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POST-EARNINGS ANNOUNCEMENT DRIFT

European evidence on market efficiency and how firm size and economic sector affect the PEAD anomaly

Master's Thesis
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Abstract

The post-earnings announcement drift (PEAD) is a financial market anomaly disputed by the researchers for 50 years. The main feature of PEAD is that investors appear to underreact to earnings announcements, which causes stock prices to drift in the direction of the earnings news for some time after the announcement. This delayed price response is at face value seen as a violation against the efficient market hypothesis, because the immediate price reaction suggested by efficient market theory remains partly absent. What separates PEAD from other financial market anomalies is the major persistency of it and despite the extensive amount of research, the exact reasons for the anomaly have remained vague.

Previous research on the anomaly has mainly focused on the U.S. stock markets, whereas international evidence of PEAD has remained scarce. In addition, most of the previous studies have focused on investor/market behavior and other firm-wise external factors as the drivers of the anomaly, while less attention has been given to the firm-related factors. Thus, the objective of this study was two-fold. First, it was examined whether and to what extent PEAD exists in the European (ex. UK) stock markets based on financial statement information released in 2018. Furthermore, it was explored how firm size and economic sector affect the magnitude and the length of PEAD.

The main findings of the study include observing statistically significant PEAD in European (ex. UK) stock markets, especially among the firms who had reported negative news compared to what was expected by the analysts. This result implies an under-reaction to earnings information, which subsequently leads to a delayed price response (PEAD). Regarding the firms who had reported positive news compared to what was expected, an initial over-reaction to the earnings information was observed. After the initial over-reaction, a price correction in the form of negative abnormal returns was found to take place. These results together provide evidence contradicting the efficient market hypothesis.

Additionally, firm size was found to be inversely related to the magnitude of PEAD, suggesting that for larger firms, there exists a more immediate price reaction after the earnings announcements. For smaller firms, in turn, the delayed price response was found to be more pronounced. The results of the analysis regarding the effect of economic sector on PEAD were, however, more unambiguous. A significant difference on PEAD was found only between Real Estate and Industrials sectors, a difference that could not be explained with firm size. Moreover, firm size and economic sector were found to be unassociated with the length of PEAD.

Keywords Post-earnings announcement drift, PEAD, market efficiency

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Tiivistelmä

Post-earnings announcement drift (PEAD) on markkina-anomalia, jonka olemassaolosta ja syistä tutkijat ovat väitelleet jo viidenkymmenen vuoden ajan. PEAD-ilmiö määritellään markkinoiden alireagointina yhtiöiden tulosjulkaisujen sisältämään informaatioon, joka puolestaan johtaa siihen, että osakkeiden hinta korjaantuu tulosjulkaisujen sisältämän tiedon edellyttämälle tasolle vasta päiviä tai jopa viikkoja julkaisuajankohtien jälkeen. Tämä viivästynyt markkinareaktio nähdään usein todisteena tehokkaiden markkinoiden hypoteesia vastaan, koska välitön markkinareaktio uuteen tulosinformaatioon ei ole tarpeeksi suuri. PEAD:n vakavuutta muihin markkina-anomalioihin nähden alleviivaa sen pysyvyys eri otosten ja ajanjaksojen välillä, sillä monet muista anomalioista ovat hävinneet ajan saatossa niiden saaman julkisuuden myötä. Huolimatta monista PEAD-ilmiötä käsittelevistä tutkimuksista, yksityiskohtaisia syitä anomalian olemassaololle ei ole pystytty esittämään.

Aikaisemmat PEAD-ilmiötä koskevat tutkimukset ovat keskittyneet pääosin Yhdysvaltojen markkinoihin kansainvälisen tutkimustiedon kustannuksella. Sen lisäksi, aikaisempi tutkimus on keskittynyt selittämään PEAD-ilmiötä lähinnä markkinoiden sekä sijoittajien käyttäytymistä hyväksikäyttäen, kun taas yhtiökohtaiset tekijät ovat jääneet vähemmälle huomiolle. Tämä tutkimus pyrkii korjaamaan edellä esitetyt epäkohdat. Tutkimuksen ensimmäinen tavoite oli selvittää, missä määrin PEAD-ilmiö on läsnä Euroopan osakemarkkinoilla perustuen vuonna 2018 julkistettuun tilinpäätösinformaatioon. Toinen tavoite oli selvittää, miten yhtiöiden koko sekä toimiala vaikuttavat PEAD-ilmiön vahvuuteen sekä pituuteen.

Yksi tämän tutkimuksen päätuloksista on se, että PEAD-ilmiö on läsnä tilastollisesti merkitsevänä Euroopan (pl. Iso-Britannia) osakemarkkinoilla etenkin niiden yhtiöiden osalta, jotka raportoivat negatiivisen tuloksen suhteessa analyytikkojen ennusteisiin. Tämä tulos kertoo alireagoinnista tulosinformaatioon, joka puolestaan johtaa viivästyneeseen markkinareaktioon. Sen sijaan positiivisen tulosyllätyksen raportoineiden yhtiöiden osalta markkinoilla oli havaittavissa ylireagointia, jonka jälkeen osakkeen hinta korjaantui negatiivisten epänormaalien tuottojen muodossa. Nämä tulokset yhdessä puhuvat tehokkaiden markkinoiden hypoteesia vastaan.

Lisäksi yhtiön koko on tämän tutkimuksen perusteella kääntäen verrannollinen PEAD-ilmiön suuruuteen, eli suurempien yhtiöiden osalta osakkeen hinnanmuodostus on tehokkaampaa tulosjulkaisun jälkeen. Tulokset liittyen toimialan vaikutukseen eivät ole yhtä yksiselitteisiä, sillä merkittävä eroavaisuus PEAD-ilmiön suuruudessa löytyi vain kiinteistö- ja teollisuussektorien väliltä. Tätä eroa yhtiöiden koko näillä toimialoilla ei pysty selittämään. Lopuksi, yhtiön koon ja toimialan ei todettu olevan yhteydessä PEAD-ilmiön pituuteen.

Avainsanat Post-earnings announcement drift, PEAD, markkinoiden tehokkuus

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1. Introduction

1.1. Background

During the vast history of financial markets, researchers across the globe have found numerous market anomalies contradicting with the core assumption of efficient market hypothesis. As defined by Schwert (2003), market anomalies in such are well-documented empirical results that are inconsistent with the maintained theories of asset-pricing behaviour. They indicate either that the markets are inefficient or that there are inadequacies in the underlying asset-pricing models. As further described by Schwert (2003), examples of the well-known anomalies include the small-firm effect (see e.g. Banz & Reingaum 1981), the January effect (see e.g. Keim & Reingaum 1983; Roll 1983), the weekend effect (see e.g. French 1980; Keim & Stambaugh 1984; Schwert 1990), the value effect (see e.g. Ball 1978; Basu 1977; Fama & French 1992) and the momentum effect (see e.g. DeBondt & Thaler 1985; Fama & French 1996; Jegadeesh & Titman 1993).

One of the most interesting findings regarding this particular field of research is that many of the popular anomalies do not eventually seem to hold between different time periods or even between different samples in the same time period. This may suggest the possibility that some or even most of the market anomalies are after all more apparent than actually real. (Schwert 2003). Despite these type of findings across various anomalies, there does exist one robust financial market anomaly whose persistence has been documented by dozens of studies, between different time periods and across various samples and countries. This anomaly is called the post-earnings announcement drfit (henceworth also PEAD), essentially the first-ever documented major accounting-based anomaly discovered initially by Ball & Brown (1968).

The main feature of PEAD is that investors appear to underreact to earnings announcements. Consequently, a company's stock price and the cumulative abnormal returns for that stock tend to drift or fluctuate in the direction of the earnings news several days or even weeks after the earnings announcement, contrary to the immidiate reaction suggested by the efficient market hypothesis. (Livnat & Mendenhall 2006; Richardson et al. 2010). This means that for firms reporting negative (positive) news compared to what was expected, their abnormal security returns tend to drift upward (downward) for some time following the earnings announcements (Scott 2015).

More originally, Bernard & Thomas (1989) defined PEAD as “the systematic pattern of a stock’s abnormal return to drift in the direction of an earnings surprise for a period of time subsequent an earnings announcement”. Hirshleifer et al. (2008) have taken a broader view themselves and define PEAD as “the tendency for stocks to earn high positive average abnormal returns in the three quarters subsequent to extreme positive earnings surprises and, more strongly, to earn negative average abnormal returns in the three quarters subsequent to extreme negative earnings surprises”. In statistical terms, market anomalies like this imply serial correlation of stock returns, whereas under market efficiency the serial correlation would equal zero (Scott 2015).

Ever since the original study by Ball & Brown (1968), the PEAD anomaly has been referred to as “the granddaddy of all underreaction events” (Fama 1998) and “the most severe challenge to financial theorists” (Brennan 1991), mainly because of its major persistence. Ball (1992) further notes that the anomaly has been replicated concistently and with increasing precision in one of the most carefully and thoroughly researched areas of the empirical financial economics literature. Taken at face value, he adds, this anomaly implies that stock markets “grossly fail the test of competitive economic theory” and challenges the assumptions underlying most of the widely-used models in the modern financial economics. Despite the five decades of research on the matter, there is still no consensus to date regarding the source(s) of the drift (Ayers et al. 2011) and it is still perceived as a puzzle from the perspective of the efficient market hypothesis (Hirshleifer et al. 2011).

1.2. Purpose & main findings

Most of the previous studies on PEAD are structured with U.S. data and focus on the effects of investor/market behaviour and other firm-wise external factors as the determinants and drivers of PEAD. More precisely, this means that the effects of trading and distinct investor groups (see e.g. Ayers et al. 2011; Hirshleifer et al. 2008), analyst forecasts and behaviour (see e.g. Li & Tse 2008; Wang 2008; Zhang 2008), liquidity risk (see e.g. Chordia et al. 2009; Sadka 2005) and trading costs (see e.g. NG et al. 2008) have been quite thoroughly examined. At the same time, less attention has been given to the firm-related factors as the possible drivers of PEAD. In addition, the comprehensive studies with U.S. data have somewhat overshadowed the limited studies considering other stock markets, so further out-of-sample research has the potential to shed new light on the anomaly. Indeed, Gerard (2012) points out that due to several data limitations, the evidence for PEAD in Europe is relatively scarce. Moreover, the research regarding PEAD is generally quite well up to date, so additional studies are able maximize their contribution to the matter by focusing on rather recently published financial information.

Thus, the scope of this study includes specifying the extent to which PEAD is present in the European (ex. UK) stock markets based on financial statement earnings information released in 2018. In addition, this study aims to determine how firm size and economic sector as the internal firm-related factors affect the anomaly in question. By doing so, this study attempts to fill in the research voids described earlier. What is however beyond the scope of this study is the portfolio construction method presented in some of the previous studies to further examine how investors could have in practice benefitted from the anomaly. As this method would require, among other details, the determination of the applicable transaction costs of forming such a specific portfolio, this study leaves at stating whether such a further examination would at all be reasonable based on the magnitude of PEAD.

This study is consequently formed based on two distinct research questions:

1. **To what extent is PEAD present in the European (ex. UK) stock markets based on financial statement earnings information released in 2018?**

2. **How well do firm size and economic sector explain the possibly observed PEAD?**

The final purpose of this study is to find an answer to the second question, which is also the main research question. The first question is a preliminary research question, which serves as a prerequisite for fulfilling the final purpose.

The main findings of this study inculde observing statistically significant PEAD in European stock markets in 2018 especially among the firms who had reported negative earnings news compared to what analysts had forecasted. This finding suggests an underreaction to earnings news among the bad news stocks, whereas an initial overreaction to earnings information was observed among the firms who had reported a positive earnings surprise. Moreover, firm size was found to be inversely related to the magnitude of the PEAD (greater size implies milder deviation from the expected returns), whereas the effect of economic sector on PEAD was found to be of more ambiguos nature. In addition, firm size and economic sector were found not to have an effect on the length of PEAD.

1.3. Methodology & structure

The empirical part of this study is divided into two sections based on the two distinct research questions. First, the magnitude and significance of the anomaly in the European stock markets were examined with an event study considering published financial statement information between 1.1.2018 – 30.9.2018 and the subsequent stock behavior. The event study was conducted with the aARC program at www.eventstudytools.com to find out the average abnormal returns (AARs) and the cumulative average abnormal returns (CAARs) for the sample stocks in the event window. The statistical significance of the AARs and CAARs was further tested with Adjusted Patell Z-test to assess the statistical significance of PEAD as a whole. This analysis was conducted to answer the preliminary research question (*Question 1*) and the methodology in detail is further described in chapter *4.1*.

Second, the firm-specific intrinsic values of the cumulative abnormal returns (CARs) as well as the firm-specific drift lengths from the event date onwards, both derived from the first phase, were explained with ordinary least squares (OLS) regression analysis. The regression analysis was conducted to answer the main research question (*Question 2*). A more detailed description considering the deployed regression models and the independent and dependent variables can be found in chapter *4.2.*

After this brief introduction to the matter, the structure of this thesis is as follows. In chapter 2, the theoretical framework of PEAD is reviewed along with previous literature regarding the anomaly. In chapter 3, the research hypotheses are constructed based on the previous research information. Empirical methods and data are elucidated in chapters 4 and 5, respectively, while chapter 6 dives thoroughly into the empirical findings and provides some discussion and limitations. Finally, chapter 7 concludes with ideas for future research.

2. Post-Earnings Announcement Drift

This chapter is organized so that the reader can get a glimpse on the anomaly from various theoretical perspectives. As a starting point, the theory of efficient markets is explained as its definition is one of the key preliminary assumptions regarding the final conclusions on how the PEAD anomaly effects the theoretical framework of efficient financial markets. In addition, the technical properties of PEAD are explained. These include the definitions for earnings surprise and abnormal returns and how the definitions of these concepts may effect the magnitude of PEAD. Moreover, this chapter sums up the previous evidence on the anomaly in different markets as well as in different time periods and goes through the main reasons proposed for the anomaly. Finally, this chapter reviews the practical implications and consequences of PEAD.

2.1. Efficient markets hypothesis

Accounting theorists began to realize the importance of the efficient securities market already in the late 1960's and since then, the theory of efficient markets has guided the related research and has had major implications for accounting as a practice (Scott 2015). As defined by Fama (1970), the primary role of the capital markets is the allocation of ownership of the economy's capital stock. He adds that generally, if market prices provide accurate signals for resource allocation, we find ourselves in the market ideal. However, the efficient markets theory itself is a model of how a securities market operates and like any other model, it does not fully capture the complexity of such a market. Thus, the relevant question is not if the markets are efficient or not but rather the degree of efficiency. That is, how close the actual markets are to the full efficiency ideal. (Scott 2015).

To assess this question, previous literature (e.g. Fama 1970; Jensen 1978; Fama 1991) has defined three different forms of market efficiency. These forms are called weak form, semi-strong form and strong form and are respectively defined as follows:

Weak form: An efficient securities market is one where the prices of the securities traded on that market at all times fully reflect *all past trading data*. In such case, technical analysis is useless and cannot generate abnormal returns.

Semi-strong form: An efficient securities market is one where the prices of the securities traded on that market at all times fully reflect *all information that is publicly known* about these securities. In such case, fundamental analysis is fruitless and cannot generate abnormal returns.

Strong form: An efficient securities market is one where the prices of the securities traded on that market at all times fully reflect *all possible information* (public and insider information) about these securities**.** Under this extreme form of efficiency, abnormal returns cannot be generated using any information, because it has already been absorbed into the security prices.

According to Scott (2015), it is quite apparent that stock prices in the real world are not reflecting the strong form of efficiency because of the high costs of elimininating all insider information. In addition, Fama (1991) points out that since there are information and trading costs present in the markets, the extreme form of the market efficiency hypothesis is surely false. Nor is the weak form very usable, because in such case the information contained for example in financial statements (e.g. in balance sheet, P/L statement, notes) would not be reflected in the stock prices, which obviously is not the case. Due to this reasoning, it is justified to use the semi-strong form of market efficiency as the baseline for the term "market efficiency".

To further assess the matter, market efficiency should not be seen as a solid state but rather as a fluctuating concept. If the markets were perfectly efficient and every investor knew it, there would be no reward in form of higher profits for collecting information. Information collection and security analysis is costly (at least when measured with opportunity costs), and if these costs are not to be compensated in form of higher (abnormal) returns, every market participant would diversify their investments to minimize the firm-specific risk and believe in current market prices. However, if no one collects or acts on information, the markets can no longer be efficient.

Regarding this issue, Grossman and Stiglitz (1980) have stated that markets can actually never be 100% informationally efficient. According to them, there must be some quantity of abnormal profits to be made to compensate the informed investors for the costs of information collection. However, in equilibrium, the abnormal profits gained by informed investors equal exactly the costs of collecting the information (Grossman & Stiglitz 1980). As further mentioned by Jensen (1978) and Fama (1991), asset prices are reflecting information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs. This is viewed as an economically more sensible version of the efficient market hypothesis (Fama 1991).

Scott (2015) notes that there are a few points about this kind of market efficiency that are particularly noteworthy. First, by definition, market prices are viewed as efficient even though they do not reflect insider information. There are persons who posses insider information and know more than the market, and they may be able to earn excess profits on their investments at the expense of outsiders. Consequently, one of the major functions of accounting in general is to convert insider information into publicly known information via timely and reliable reporting practices. Nevertheless, Scott (2015) continues, investors will still be worried about the existing possibility of insider trading.

Second, it is pointed out by Scott (2015) that market efficiency is a relative concept and the market will subsequently be efficient relative to the amount of publicly available information. It should be further emphasized that even though markets are viewed as efficient, there is absolutely nothing in the definition suggesting that the stock prices are reflecting the real underlying values of the stocks. For example, during the market meltdown in 2007-2008, the market prices of asset-backed securities and the firms that issued them clearly overstated their value in retrospect. However, the important question regarding the semi-strong form of market efficiency is whether at that time the prices of such securities reflected all publicly available information or not. (Scott 2015).

Finally and most interestingly, Scott (2015) notes that if the markets are efficient, serial correlations of stock returns should not exist and a security's market price should randomly fluctuate over time. If a firm reports good news (bad news) today, its stock price should immidiately rise (fall) to reflect these news. If, however, the stock price continues to rise or fall during the following days in the absence of any further news, it can be viewed as evidence in favour of market inefficiency. (Scott 2015). This inherently leads to the conclusion that if PEAD is defined as the observed serial correlation of abnormal returns in the post-earnings announcement period (e.g. Bernard & Thomas 1989; Hirshleifer et al. 2008; Livnat & Mendenhall 2006; Richardson et al. 2010), the anomaly is at face value an offense against the efficient market hypothesis.

2.2. Earnings surprise

Before the actual magnitude of PEAD can be measured, firms in a particular sample are typically divided into at least two groups: firms who have reported good news (positive earnings surprise) and firms who have reported bad news (negative earnings surprise) compared to what was expected. The terms "good" and "bad" are relative concepts, so it is important first to determine the baseline to which the reported earnings are compared to. It should be noted that a negative (positive) earnings surprise does not in such imply that a particular firm recorded a loss (profit). Had a firm reported a loss of one million euros, the surprise would still be viewed as positive if a more severe loss was expected. Similarly, had a firm reported a profit of one million euros, the surprise would still be viewed as negative if a larger profit was expected.

In previous literature, the two most common concepts used regarding this matter are the seasonal random-walk based earnings surprise and the analyst forecast based earnings surprise. They can be further calculated either as absolute surpises or as relative surprises. In the case of relative surprises, the commonly used term is Standardized Unexpected Earnings (SUE), which refers to the method that the absolute surprise is stanrdardized for example with the firm's stock price. This, in turn, makes it easier to compare the earnings surprises among different companies.

Seasonal random-walk based earnings surprise or, interchangeably, time-series model of expected earnings is defined in previous studies (e.g. Ayers et al. 2011; Bernard & Thomas 1989, 1990; Doyle et al. 2006, Livnat & Mendenhall 2006) as actual earnings minus the expected earnings scaled with a particular variable, for example stock price:

$$RW = (EPS_t - EPS_{t-4})/P_{t-1} \tag{1}$$

where

RW = seasonal random-walk based earnings surprise

EPS_t = actual earnings per share (EPS) for quarter t

EPS_{t-4} = actual EPS for quarter $t-4$

P_{t-1} = stock price at the beginning of quarter t

Similar to *Equation 1*, the analyst forecast based earning surprise is measured as holding the reported earnings and the price deflator constant, while replacing the proxy for expected earnings with an analyst forecast (eg. Ayers et al. 2011; Livnat & Mendenhall 2006):

$$AF = (EPS_t - AF_t)/P_{t-1} \tag{2}$$

where EPS_t and P_{t-1} are defined as in *Equation 1* and

AF = analyst forecast based earning surprise

AF_t = analyst forecast of EPS_t

Henceworth, the seasonal random-walk based earnings surprise is being referred to as the RW surprise and the subsequent post-earnings announcement drift as the RW drift. Similarly, the analyst forecast based earning surprise is being referred to as the AF surprise and the subsequent post-earnings announcement drift as the AF drift.

As stated, the two models differ from each others only in terms of the proxy used for expected earnings. With the RW surprise, the most common practice is to use the actual earnings the year before as the proxy for expected earnings but with AF surprise, it is possible to use either the most recent analyst forecast (e.g. Ayers et al. 2011) or the consensus forecasts of all analysts (e.g. Livnat & Mendenhall 2006). However, Brown and Caylor (2005, see Brown & Kim 1991) argue that the most recent analyst forecast is a better suited proxy for two distinct reasons. First, the effects of pre-announcements are mitigated when using the most recent forecast and second, the most recent forecast is evidently more closely related to the stock price reaction to earnings announcements.

With U.S. data from 1987 to 2003, Livnat & Mendenhall (2006) examined the potential differences in abnormal returns generated by portfolios formed based on these competing measures of earnings surprise. They reported that although the majority of prior researchers had used the seasonal random-walk based forecast measure, the drift using the analyst-based forecast was actually consistently and significantly larger. According to the researchers, this result implies that either these two measures of forecasting are both capturing different forms of stock market mispricing or that some of the prior explanations for the anomaly (e.g. overreliance on RW forecasts) may be too hasty.

Doyle et al. (2006) have also shown similar results with U.S. data ranging from 1988 to 2000. By defining earnings surprise relative to an analyst forecast rather than a time-series (seasonally random-walk based) model, they documented abnormal returns in the event window that were much larger and more persistent than shown in previous studies. Interesting from the perspective of this particular study is that the results obtained by Doyle et al. (2006) were not concentrated in a few industries and that firms with extreme earnings surprise were generally found to be smaller than the average firm.

In addition, Doyle et al. (2006) found that the firms with extreme earnings surprises tended to be "forgotten" stocks with relatively high book-to-market ratios, low analyst coverage and high analyst forecasts dispersion. Moreover, firms with extreme positive earnings surprises tended to have persistent earnings surprises in the same direction for three subsequent years. Abnormal returns were documented to be highest when the transaction costs were highest and interest of institutional investor is lowest, consistent with the idea that market inefficiencies are more prevalent when frictions make it difficult for large (sophisticated) investors to exploit the inefficiencies. Finally, the results of Doyle et al. (2006) are reported to hold even after controlling for risk (as measured by beta, firm size and book-to-market ratio) and after controlling for other market anomalies such as price momentum, accruals, pro forma exclusions and PEAD based on RW surprise.

2.3. Previous evidence from U.S.

According to Ball (1992), the PEAD anomaly is scientifically so indisputable that the contentious issue is not anymore the existence of the anomaly but its explanation. Although the vast amount of literature and studies on the matter, the proposed reasons for the anomaly are still manyfold and there is no single consensus among researchers regarding the source(s) of the drift (Ayers et al. 2011). To gain a more comprehensive understanding on what probably causes the anomaly, this study approaches the dispute by dividing the proposed reasons into two main aggregates, which can be furthermore divided into different subparts. These main aggregates are the perspective of poor risk adjustment and the perspective of market inefficiency, defined respectively as follows (e.g. Ayers et al. 2011; Bernard & Seyhun 1997; Bernard & Thomas 1989; Richardson et al. 2010):

Poor risk adjustment perspective: The abnormal returns occur due to some unindentified risk factors and thus, the "abnormal" returns are nothing more than a justifiable compensation for that unaccounted amount of risk, in line with the efficient market theory.

Market inefficiency perspective: Market participants are unable to fully incorporate the future predictability of the true earnings time series into their decisions, which creates abnormal returns and implies market inefficiency.

Before digging into the vast evidence on the matter and making conclusions about the most plausible explanation, a few points about testing market efficiency should be noted. Bernard and Seyhyn (1997) point out that regarding the dispute of whether PEAD is more likely resulting from market inefficiencies or from failures to control for risk, there exists an underlying disorder called the joint hypothesis problem. First pointed out by Fama (1970), the joint hypothesis problem suggets that it is impossible to test market efficiency without silmultaneously assuming and testing also some model of expected returns. Thus, it is "not possible to assure that evidence apparently at odds with market efficiency is not actually an indication of shortcomings in the hypothesized asset pricing model and its characterization of risk" (Bernard & Seyhun 1997). The joint hypothesis problem in such leads to the unwieldy conclusion that market efficiency *per se* is an untestable hypothesis (Fama 1991).

To illustrate the difference, it can for the sake of simplicity be assumed that a trading strategy producing abnormal returns has been found. If, for example, the capital-asset pricing model (CAPM) has been used to determine the magnitude of abnormal returns in the first place, two alternative interpretations are possible. First, it can be assumed that the CAPM as the underlying model is right and true evidence of market inefficiency has been found. Second, in the absence of any further information, it can as well be concluded that CAPM as the underlying assumption is misspecified and once a well-specified risk correction to the model is made, the "abnormal" returns disappear. This in turn is an argument in favour of the efficient market theory. The joint hypothesis problem is consequently present also in all of the following studies on PEAD, and because of that problem, "precise inferences about the degree of market efficiency are likely to remain impossible" (Fama 1991).

2.3.1. The perspective of poor risk-adjustment

As stated, the first main aggregate of reasons for PEAD is that following the earnings announcements, the subsequent abnormal returns occur due to some unidentified risk factors. Because of this, the "abnormal" returns are no longer seen as abnormal but as a normal compensation for increased risk, in line with the efficient markets theory. This view originally rose and gained attention because given how visible and widely followed earnings announcements are, attributions of such evidence to market inefficiency were greeted with skepticism (Bernard & Seyhun 1997). Ball (1978) has argued that there are reasons to believe *ex ante* that stock markets are efficient, but even in an efficient market, trading strategies based on earnings numbers may appear to generate abnormal returns due to the misspecifications in the model used to measure the abnormal returns. Foster et al. (1984) as well as Ball et al. (1993) have further provided substancial but at the same time ambivalent evidence regarding this argument.

In their study, Foster et al. (1984) had two alternative approaches in analyzing the post-announcement behaviour of stock returns. The first was an earnings-based model (EBM), in which the unexpected earnings of NYSE and AMEX firms (measured by using a statistical earnings forecast and scaled by the standard deviation of prior forecast errors) were compared to the cross-sectional distribution of scaled unexpected earnings for the prior quarter. According to their standing relative to that distribution, firms were assigned to ten different portfolios. Finally, the size-adjusted abnormal returns of those ten portfolios were plotted over the 120 trading days surrounding the earnings announcement date. The second approach assigned firms to portfolios on the basis of firms' estimated abnormal returns over the 60 days prior to the earnings announcement day (including the actual earnings announcement day), labeled as the security-return model (SRM).

The essential result of Foster et al. (1984) is that the PEAD was found to be significant only under the earnings-based model, but not under the security-return model. The conlcusion drawn by some researchers based on these results is that the PEAD might in fact reflect some problems in risk measurement: "Using the SRM method of forming portfolios yields no unusual return behaviour following the earnings announcement and suggests again that the results of previous studies are caused by a misspecified pricing model" (Bernard & Thomas 1989, see Dyckman & Morse 1986).

However, Bernard & Thomas (1989) add that these kind of conclusions may be too rushed. They state that the results obtained by Foster et al. (1984) are "consistent not only with certain explanations under which the drift represents a risk premium but also with certain other explanations where the drift reflects a delayed price response", ergo market inefficiency. More specifically, Bernard & Thomas (1989) show that if there exists a delayed price response to earnings announcements and the fraction of the delayed total response varies sufficiently across firms, it is possible to simultaneously detect a drift in the EBM test but not in the SRM test. As a result, it is suggested by Bernard & Thomas (1989) that rather than discriminating between CAPM misspecification and delayed price response, the results of Foster et al. (1984) should be viewed as imposing restrictions on the nature of CAPM misspecifications as well as on the delayed price response. Hence, after viewing these results, the overall question of which of the two main aggregates after all causes PEAD remains unanswered.

Addressing the same matter, Ball et al. (1993) pointed out that since some prior studies assumed betas to be stationary in the CAPM used to calculate the abnormal returns, this caused a bias in estimated abnormal returns. According to them, this bias occurs due to the fact that betas are actually shifting upward for firms with high unexpected earnings and downward for firms with low unexpected earnings. To resolve this problem, they used an estimation approach permitting the betas in the CAPM to shift annually. After allowing betas to move this way, they found that PEAD was no longer significant. However, a more recent test conducted by the very same researchers with quarterly (not annual) data indicated significance in PEAD even after allowing beta to shift (Bernard & Thomas 1989), so the evidence is also hereby mixed.

More recently, Bernard & Seyhun (1997) verged on the matter by using a stochastic dominance approach. They handled the joint hypotheses problem described earlier by making only two very mild assumptions about asset pricing. First, it was assumed that investors in general prefer more wealth to less and second, investors in general were assumed to be risk-averse. If the former was assumed, the first-order stochastic dominance of one security over another would imply an arbitrage opportunity. Second-order stochastic dominance would also imply an arbitrage opportunity, as long as the latter assumption holds. (Bernard & Seyhun 1997).

Before going into the results of that study, it is important to note a few things about the methodology and framework in question. According to Bernard & Seyhun (1997), the problem with stochastic dominance testing is that it demands so much of the data that even clear market inefficiencies might fail to produce trading strategies that are stochastically dominant. However, they reason that if there are instances where stochastic dominance *can* be evidenced, then such a conclusion should eliminate any reasonable concerns that the market anomaly in question could be due to a failure to control for risk. To prove their point, the researchers focused on a longer-term (3 to 6 month) PEAD, because the risk adjustment explanation is more plausible when using a wider time frame: "only over the longer interval does the drift (resulting from failures in risk adjustments) plausibly exceed normal transaction costs" (Bernard & Seyhun 1997). In other words, they used a time frame in favour of the risk adjustment explanation, which emphasizes the importance of the following results.

With their portfolio construction, Bernard & Seyhun (1997) found undisputable evidence that the porfolio of stocks with standardized unexpected earnings in the highest decile dominated the portfolio in the lowest decile by first-order stochastic dominance. To further explain the meaning of that result, it is worthwhile to note that the estimated probability of obtaining such a result by chance is less that 0.5 %. Even after allowing for 3 % round-trip transaction costs, the highest SUE decile portfolio dominated the lowest by second-order stochastic dominance. This result, according to the researchers, "should eliminate any reasonable concern that risk adjustment problems explain the phenomenon" and "constitutes compelling evidence of market inefficiency". Finally, they state that an understanding of this anomaly seems to indeed require either some model of inefficient markets, or identification of some other than transaction cost that delay the absorption of accounting information in stock prices. Therefore, the attempts to explain PEAD would be most fruitfully focused on reasons why market prices do not reflect all available information. (Bernard & Seyhun 1997). The following section attempts to shed light and provide answers for this question.

2.3.2. The perspective of market inefficiency

As no unanimous evidence for the claim that PEAD exists due to the failures in risk measurement has been found to date, recent studies have focused more on the market inefficiency perspective. This perspective is driven by the attempts to identify possible reasons preventing the absorption of public information into stock prices. Eventually, it all seems to come down to the fact that information in the modern capital market is quite endless by nature, which in turn leads to the conclusion that some market participants remain more informed than others. In addition, as from the investors' perspective time and attention are valuable resources, more is generally known about some companies than others.

Investor sophistication

An underlying assumption and a starting point for hypothesis development in the studies considering the level of investor sophistication as the driver of PEAD is that individual investors as a group are generally seen to be less sophisticated than institutional investors. Thus, PEAD as a sign of market inefficiency may result more from the trading behaviour of individual (unsophisticated) investors than from that of the institutional (sophisticated) investors. (e.g. Bartov et al. 2000; Doyle et al. 2006; Hirshleifer et al. 2008).

First, Doyle et al. (2006) have documented the abnormal returns subsequent to earnings announcements to be highest when the interest of institutional investors in a company is lowest. This suggests that institutional investors, who are perceived as sophisticated and well-informed, are generally able to drive the price reaction to occur more immidiately after the earnings announcements. In addition, the researchers showed that returns for PEAD trading strategy are larger the higher the bid-ask spread and the lower the average trade size or the number of trades are. These results are consistent with the idea that market inefficiencies are more prevalent when frictions make it difficult for large (sophisticated) investors to exploit the inefficiencies (Doyle et al. 2006).

Supporting these results, Bartov et al. (2000) found that PEAD is diluted when a greater proportion of a firm's stocks is held by institutional investors. They find that especially the

RW drift decreases when the level of institutional ownership increases and conclude that institutional investors seem to improve the efficiency with which RW earnings surprises are priced. However, they do not investigate the AF drift or specifically link investors trades to the RW drift. In addition, Scott (2015, see Ke & Ramalingegowda 2005) notes that some institutions actually seem to earn arbitrage profits by trading on PEAD, but other strategies such as buy & hold or momentum trading dominate the PEAD strategy so that the amount of their trading on PEAD is well short of what would be needed to arbitrage the anomaly away.

In contrast, Hirshleifer et al. (2008) examined all trades made by a sample of individual investors through a major discount brokerage firm in US from 1991 to 1996 to find out if PEAD can be attributed to individual (unsophisticated) investor behaviour. They found, on the contrary to what was hypothesized, that individual investors as a group do not seem to drive PEAD. One of the provided reasons for that was the maybe too simple dichotomy between sophisticated institutional investors and unsophisticated individual investors. They mention that it is worthwhile to note that sometimes institutions trade poorly with respect to anomalies and that there are also individual investors who can be perceived objectively as smart market parcitipants. However, the researcher conclude by asking that if individual investors and institutional investor do not seem to drive PEAD, who does?

Hirshleifer et al. (2008) as well Bartov et al. (2000) further point out that there is actually mixed evidence of whether the level of institutional shareholding is after all a good enough proxy for investor sophistication, as a good proxy in a research design should essentially be interchangeable with the variable it is meant to measure. If that is not the case, the framework of that design will be biased and corrupted. In addition to the level of institutional shareholding, another ambivalent proxy used for investor sophistication is the trade size. According to Richardson et al. (2010), the quality of the trade size proxy is also questionable because over the last decade, the growing use of algorithmic trading among institutional investors has resulted in trade size getting smaller and smaller. This change in market microstructure has, according to them, made it harder to attribute small trades solely to individual (less sophisticated) investors.

A compelling detour around this mixed evidence can be found from the technical properties of the anomaly and the subsequent definitons of RW and AF drift. Livnat & Mendenhall (2006) have argued that "if researchers do not understand how the magnitude of the drift depends on the specification of the earning surprise, they stand little chance of understanding the nature of the anomaly". Whereas the already referred studies tried to attribute the PEAD as a whole to the distinct sets of investors, recent studies have taken the words of Livnat and Mendenhall (2006) into account and gone further to divide the anomaly into parts to find meaningful and clarifying results.

Ayers et al. (2011) have conducted a comprehensive study regarding this matter. They examined whether the two distinct drifts (RW drift & AF drift) are possibly attributable to different identifiable subsets of investors. Although prior studies (see e.g. Battalio & Mendenhall 2005; Bhattacharya 2001; Walther 1997) had already found that small traders were more likely to trade based on RW surprise and large traders were more likely to trade based on AF surprise, the work by Ayers et al. (2011) is actually the first study ever to link the subsequent drifts to these two different groups of investors.

Using U.S. trade and quote data of trades executed from 1993 to 2005, the researchers found compelling results in line with what was hypothesized: only small traders seem to systematically trade in the direction of the RW surprise after the earnings announcements and only large traders seem to trade in the direction of the AF surprise after earnings announcements. This evidence, according to the researchers, is consistent with the two distinct sets of traders explaining, at least in part, the two different forms of PEAD.

In addition, Ayers et al. (2011) have further documented some interesting remarks about the two distinct drifts. First, they show that when traders trade more intensely in the direction of the earnings surprises during the announcement period, the magnitude of the subsequent drift is lower. This holds true with both of the drifts. In addition, they find that the RW and AF drifts are actually qualitatively different from each others. Large traders seem to trade more at the early stage of the post-announcement period, whereas small traders seem to spread their trades troughout the 60-day post-announcement period.

Moreover, they show that small trades around subsequent earnings announcements are actually predictable based on lagged one-to-four quarter RW surprises, but that there is no evidence of large trades at earnings announcements being associated with prior AF earnings surprises. This, according to the study, suggests that the RW drift but not the AF drift is largerly explained by small or unsophisticated investors' failure to recognize the time-series property of earnings (originally suggested by Bernard & Thomas 1989) and therefore presents investor naivete.

Finally, it is concluded by Ayers et al. (2011) that the AF drift has decreased in recent years (1999 onwards), while the magnitude of the RW drift has not changed. They point out that this result is consistent given the relatively new discovery of and the little attention that the AF drift has received in earlier years. This result adds to the work by Doyle et al. (2006) and Livnat & Mendenhall (2006), who at that time found the AF drift to be significantly larger than the RW drift.

Limited attention

Investors in general are seen to be restricted by limited amount of time and limited cognitive resources when making investment decisions (Dellavigna & Pollet 2009) and, because minds are finite, attention must be allocated selectively (Hirshleifer et al. 2009). Regarding this constraint, Hirshleifer et al. (2009) have constructed a framework called the investor distraction hypothesis. They present that as individuals aim to process multiple information sources at the same time, their performance will inevitably suffer. This suggests that an effort by an investor to process earnings announcement information and understand its implications for the profitability of a firm may be obstructed by additional news drawing attention towards other companies. Thus, greater amount of distraction suggests more severe underreaction to the earnings information, which leads to the realization of a weaker immediate price reaction and stronger post-earnings announcement drift. (Hirshleifer et al. 2009).

When testing the investor distraction hypothesis with U.S. data ranging from 1995 to 2004, Hirshleifer et al. (2009) found PEAD to be much stronger when the earnings announcements occured on days with many competing announcements. For high-news days, the interdecile spread of the 60-day cumulative abnormal returns between high and low earnings surprise firms was found to be 7.2%, whereas for low-news days the same spread was only 2.7%. Further analysis made by the researchers showed that PEAD is stronger for high-news days also after controlling for other possible determinants of the drift. Moreover, they observed that also the abnormal trading volume response to earnings was significantly weaker when the earnings announcement occured on a high-news day. These results provide strongly supportive evidence for the presented investor distraction hypothesis.

Dellavigna and Pollet (2009), in turn, examined the effects of limited attention on PEAD by comparing stock market reactions to earnings announcements occuring on Fridays to those occurring on other weekdays. The rationale behind the study was that if investors are distracted by the weekends as assumed, the initial reaction to Friday earnings surprises should be less pronounced. In addition, as the information content of the announcements should eventually be absorbed into the stock prices, the delayed price response (PEAD) should be of greater magnitude for the Friday announcements.

Taking advantage of U.S. data ranging from 1995 to 2006, Dellavigna and Pollet (2009) found that the immidiate stock price response was on average 15% lower for Friday announcements than for the announcements occurring on other weekdays. In addition, the delayed price response was found to be 60% and 40% of the total price response for Friday and non-Friday announcements, respectively. These results imply that investors indeed are distracted by weekends (in addition to other earnings announcements), which in turn suggests intraday variation in market efficiency. This study also further adds to the previous results regarding the weekend effect anomaly (see e.g. French 1980; Keim & Stambaugh 1984; Schwert 1990).

In guiding the seemingly roaming attention of the investors, analysts and management seem to have an important role. Drawing on a sample of US firms from 1996 to 2002, Zhang (2008) found out that if analysts revised their earnings expectations for the next quarter within two days after the current earnings announcement, the current PEAD was diluted compared to firms for which the forecast revisions took a longer time. These results suggest that with responsive analysts, the market reaction happens more immidiately after the earnings announcement while the delayed price reaction is decreased (Zhang 2008). Vice cersa, Doyle et al. (2006) documented that extreme PEAD seems to go hand in hand with high analyst forecasts dispersion, implying that the investors simply do not have the time or the necessary abilities to make up their minds about the "right" analyst forecast on which to base their investment decisions. Further, they also documented the drift to be stronger when the analyst coverage was lower (Doyle et al. 2006).

In addition to the analysts' forecasts, Zhang (2012) notes that also many managers release a forecast of next quarter's earnings at the same time they report the current earnings. As these bundled announcements have become more popular in recent years, he adds, it is relevant to examine also their effect on PEAD. With a sample of US firms from 1997 to 2007, Zhang (2012, see also Li & Tse 2008; Wang 2008) showed that PEAD over the next quarter is greatly reduced when market participants correctly expect the accuracy of manager's *ex ante* forecast and base their investment decisions on that.

Another outcome of the limited attention aspect is that when collecting information, investors will primarily concentrate on the information that is readily available. This in turn implies that the "bottom lines" of the financial statements are more important than the notes or information reported elsewhere in the financial statements (Scott 2015). Hirshleifer and Teoh (2003) note that there actually is intense concern as to the form of disclosure, even when the information content of the alternative formats is identical. Inattention seems foolish in their setting, as it was found by the researchers that investors in general lose money by ignoring certain aspects of the economic environment. However, they add, as time and attention are costly, such behaviour may be viewed as reasonable.

Ahmed et al. (2006) have further provided empirical support on this matter as they studied a sample of U.S. banks disclosing derivatives as supplementary information prior to the 1998 SFAS 133 standard, and valued them at fair value in their financial statements proper subsequently to make a comparison regarding the value relevance and the subsequent market effect. They found no significant share price reactions when the derivatives were disclosed as supplementary information, but a significantly positive reaction when the derivatives were disclosed at fair value in the balance sheet. This result strongly contradicts with the efficient market theory suggesting that the location of the information is irrelevant. Furthermore, it underlines the concern about the form of the disclosure pointed out by Hirshleifer and Teoh (2003).

These results together add to the somewhat ironic fact that more public information may sometimes lead to less efficient markets, while the location and form of the information also seem to affect the investors' beliefs. Richardson et al. (2010) point out that the role of information on PEAD is indeed two-folded: previous literature (see e.g. Kimbrough 2005; Levi 2008) finds that the anomaly is weaker when there is more detailed information available about the earnings release but, on the contrary, Hirshleifer and Teoh (2009) find (as described) that the anomaly is more pronounced when there is more earnings information provided to investors at the same time. This suggests that investors appreciate more detailed information to a certain extent, but can only handle so much when multiple sources of such detailed information are available.

Gerard (2012) adds to this that although prior studies have focused on the earnings surprise, it should be noted that important non-earnings information is also released at the time of the announcements. This information can occur in the form of conference calls or press releases, while the different components of earnings (e.g. sales and operating margins) also include relevant knowledge. Therefore, to the extent that the abnormal returns capture different earnings and non-earnings related news, it can be argued that they are a broader measure of market surprise than the traditional proxies. (Gerard 2012).

Because the relevant information is scattered and the investors' attention remains limited and distracted, the role of the analysts and management in the modern financial markets shall not be overlooked as they seemingly are able to act as a link between the investors and the sources of the financial information. The results described above also underline the responsibility of analysts and management, as investors do seem to listen and base their decisions on the information provided by them. By acting timely, analysts and management can drive the information to be absorbed into the stock prices faster, causing PEAD to be diluted. Vice versa, these empirical results create an incentive for the management to hide bad news by announcing them during periods when the markets' attention is low or the level of investors' distraction is high. Similarly, they are able to highlight good news by announcing them during periods of few other earnings announcements (see e.g. deHaan, Shevlin & Thornock 2015).

All in all, the fact that investors have to selectively allocate their time and cognitive resources seems to provide a plausible explanation for the initial market underreacton and the subsequently occurring PEAD. Investors in general do face a cost/benefit -tradeoff regarding what information to acquire and thus, some investors remain more informed than others. This heterogeneity regarding the possessed information, i.e. the level of investor sophistication, evidently provides at least a partial explanation for the qualitatively quite different RW and AF drifts. However, the proxies used for investor sophistication remain somewhat imperfect. At the same time, complete information of the markets remains impossibly gathered and more remains known of some companies than others.

To conclude, the reason for the existence of PEAD still remains heavily debated despite having been extensively researched since its discovery about 50 years ago. As prior research is able to offer little support for the risk-based explanation or potential flaws in research design (Gerard 2012), more recent U.S. evidence seems to be more consistent with the market inefficiency explanation (Zhang 2012). Gerard (2012) further notes that the current belief for PEAD is that it is indeed caused by some form of underreaction to the earnings announcement information but that the exact nature of the underreaction remains vague.

2.4. Evidence outside the U.S.

Turning to international evidence, Barber et al. (2013) have examined the existence of PEAD in 46 countries (excluding the U.S.) using the annual earnings announcements from 1991 to 2010. They estimated that the average monthly raw return to a strategy of investing in a portfolio of stocks expected to announce earnings during the month and shorting an equal dollar amount of a portfolio of expected non-announcers is 7.2% p.a. It should be noted that this kind of porfolio is not constructed based on the magnitude of the previous earnings surprises (as in most of the previous studies), but is simply formed based on whether the firm in question is expected to release their earnings during the month or not.

According to Barber et al. (2013), an investment in the long porfolio offset by a similar position in the short porfolio would have yielded 314% in the period from 1991 to 2010, whereas a investment in a global portfolio, equally weighted by country, would have yielded 264% in the same period. In addition, the long-short portfolio had a 40% greater Sharpe ratio than the global portfolio. The researchers also point out, similarly to Scott (2015), that the amount of capital deployed to exploit PEAD in global markets might be less than for other anomalies, since the portfolio is hereby limited to those firms expected to release earnings during the month in question.

Among the other main findings of Barber et al. (2013) are that a major part of the premium is realized prior to (rather than after) the earnings announcement and that the higher pre-announcement returns are accompanied by reduced volume. In addition, they find that the level of idiosyncratic volatility spikes in the three days centered on the announcement date. They also extended their analysis to interim announcements, among which they did not find "any reliable evidence of a premium" in contrast to the annual announcements. To explain these results, the researchers show that the level of abnormal idiosyncratic volatility around the interim announcements is much smaller compared to that of the annual announcements and is only marginally significant. This is in contrast with the previous work on the matter (see Frazzini and Lamont 2007), whereby a significant premium for annual announcements as well as interim announcements was found in the U.S. (Barber et al. 2013).

Booth et al. (1996) provide interesting evidence of PEAD from the Finnish perspective. Their purpose was to find out whether the behaviour of the post-announcement returns differs between firms who naturally smooth and do not smooth their income in Finland. The results of the study suggest that the PEAD is stronger for firms with positive earnings surprise compared to those with negative earnings surprise (consistent with U.S. evidence), and that most of the return difference is due to the market reaction to the earnings surprises of the firms that do not have smoothened income series. The researchers suggest that hence, at least a part of the PEAD in Finland can be explained by information processing costs.

Adding to that study, Booth et al. (1997) also examined the role of different income levels as the drivers of PEAD in Finland. They reason that as the Finnish accounting practices allow the firms to manage their earnings in different ways (mainly for tax purposes), income levels other than reported earnings might also contain value relevant information for investors. The results of the study show that the net profit in the income statement based on Finnish bookkeeping legislation cannot explain the PEAD, but several different income measures are important in generating post-announcement abnormal returns. The researchers also point out that generalizations for the PEAD studies from one market to another should be carried out cautiously due to the different accounting systems in different countries.

Further, leaning on the argument that usually emerging markets are seen as less efficient than developed markets, Griffin et al. (2010) studied the role and magnitude of PEAD in emerging stock markets taking advantage from stock data between 1994-2005. They found that the anomaly was present in 15 of 38 stock markets for which they had announcement data and that the abnormal returns associated were not larger in emerging markets when measured on a relative scale. More precisely, in the six moths following the earnings announcements, they found that the GN stocks earned 1.6% above the market return in developed countries and 5.1% above market in emerging markets. BN stocks were found to earn -2.5% and 0.9% compared to market return in developed and emerging markets, respectively. Thus, the high minus low PEAD for six months was 4.1% in developed markets and 4.2% in emerging markets. Griffin et al. (2010) conclude that even though there are notable absolute differences between the returns, a trading strategy aiming to exploit the anomaly as a whole would have yielded returns of similar magnitude in developed and emerging markets.

In addition, Gerard (2012) studied the PEAD in Europe with a sample consisting of stocks listed in FTSE All-World Developed Europe Index from 1997 to 2010. In line with previous U.S. studies, they found that the abnormal returns around the earnings announcement were positively related with future returns. Firms with positive surprise in one quarter were found to surprise the market in the same direction up to one year after the announcement. Further, he demonstrated that stocks with high abnormal volume around the earnings announcements outperformed low abnormal volume stocks for up to 90 days after the announcement. In addition, it was showed that the anomaly generated larger premiums especially when information uncertainty was larger. The abnormal return and the abnormal volume effect were both found to be stronger within stocks that experience highest levels of idiosyncratic volatility.

More originally, Liu et al. (2003) examined the PEAD in UK stock markets, based on the preliminary evidence (see Hew et al. 1996) considering London Stock Exchange. Using data ranging from 1988 to 1998, the main finding of Liu et al. (2003) was that whatever the measure of earnings surprise (RW or AF surprise) used, there is significant evidence of post-announcement abnormal returns in the UK. They also find evidence supporting the previous results from U.S. that markets generally “fail to realize the full implications of current earnings for future earnings” and that the drift following earnings announcements “occurs disproportionately around the next earnings announcement” The researchers further add that a market inefficiency replicated in more than one country unambiguously points to a systematic failure in the way the markets are processing the information and that “the PEAD phenomenon constitutes a clear rejection of efficient market hypothesis”. (Liu et al. 2003).

2.5. Implications

As discussed in the prevoius sections, the PEAD anomaly is not something that can be overlooked or underestimated from either theoretical or practical viewpoints. Scott (2015) further emphasizes the fact that it is important to note the significance of this anomaly, because due to its existence, sophisticated market parcitipants can earn arbitrage profits by modifying a diversified investments strategy. The resulting investment strategy simply includes buying good news stocks and selling short bad news stocks on the day the earnings are announced. If these two kinds of stocks and the subsequent returns of these stocks were perfectly uncorrelated, the combined portfolio constructed this way would be riskless as all price changes other than those arising from PEAD would be cancelled out. Thus, the investor would earn a riskless arbitrage profit as the value of the good news (bad news) stocks drifts upward (downward) over the following day/weeks/quarters. Scott (2015) further notes that proceeds from the short sales could be used to buy more good news shares (among which the serial correlation in subsequent quarters is strongest), so little if any capital is initially required.

In previous studies, porfolio constructions like these are very common to prove the practical significance of PEAD. There is lots of evidence that this kind of strategy, with minor modifications depending on the particular study, would indeed have resulted in arbitage profits. Originally, drawing on US data from 1974 to 1986, Bernard & Thomas (1989) documented that following a strategy similar to what was just described (based on RW surprises) and holding on to the stocks for 60 days, an investor would have earned an average return of 18% p.a. above the market return, before transaction costs. More recent studies have been able to regenerate these results with varying degrees of success.

Complementing these results, Doyle et al. (2006) reported a hedge portfolio return of 14% in the year following the earnings announcements and 20% over the following two years. Their portfolio took a long position in the top decile of AF surprises and a short position in the bottom decile of AF surprises, and their results held even after controlling for risk (as measured by beta, size and book-to-market ratio) and other market anomalies. Interestingly, they also report a combined portfolio strategy whereby intersecting the PEAD strategy with an accruals strategy roughly doubles the returns while also greatly reducing the number of stocks in the portfolio.

Narayanamoorthy (2006) further argues that the positive serial correlation between current and following quarters' seasonal earnings changes will essentially be higher for good news firms than for bad news firms. This results from the fact that when conservative accounting policies are in use, at least some of the bad news is caused by writedowns effecting the net income. This, in turn, will force future reported earnings upwards, as for example a writedown of plant and equipment reduces future depreciation and amortization costs. For these firms, an increase in future earnings consequently works against the positive serial corrrelation of current and future seasonal earnings changes, which is at the heart of PEAD (Scott 2015). Further argued by Narayanamoorthy (2006), the good news firms have less likely suffered from conservative writedowns, so there should be more profits to be made from investing only in good news firms (given PEAD exists). Indeed, she was able to construct a porftolio yeilding even more than the market return + 18% p.a. obtained by Bernard and Thomas (1989).

Contradictory evidence to the matter is provided by NG et al. (2008), as they studied the effect of transaction costs on the PEAD strategy returns with a large U.S. sample ranging from 1988 to 2005. They measured the transaction costs as the sum of bid-ask spread and commissions and found that when taking a long position on the GN stocks and a short position on the BN stocks, the abnormal returns for three months were actually negative after deducting the applicable transaction costs. When holding the positions for 12 months, the returns were not necessarily negative but still insignificantly different from zero. They also found that the magnitude of PEAD was strongly related to the amount of the transaction costs, as the stocks with highest transaction costs faced the strongest PEAD. Supporting evidence for this result was also found by Doyle et al. (2006), as they similarly documented the abnormal returns to be highest when the transaction costs were highest.

However, neither these nor the above described studies took a stand on whether a more short-term PEAD strategy would have, net of cost, resulted in arbitrage profits.

To conclude, there is mixed evidence regarding the question of whether investors could have in practice benefitted from the PEAD anomaly. Scott (2015) notes that as the arbitrage strategies in general include lots of buying, selling and short selling of stocks, investors exploiting these kinds of strategies face high brokerage costs compared to other market strategies. If the particular stocks that are traded are illiquid, the stock price may rise upon buying and fall from short selling, creating an additional cost together with the possible bid-ask spread. In addition, time and effort is required to initially develop the necessary expertise as well as to continuously monitor the market, which further creates expenses at least in form of opportunity costs. (Scott 2015). Indeed, Richardson et al. (2010), using more comprehensive measures of transaction costs, have reported that strategies aiming to exploit the PEAD as well as the accruals anomaly yielded essentially zero returns (net of cost) during the period 2003-2008. For further studies verging on the matter, the determination of the applicable transaction costs (especially for a large sample of stocks) remains a challenge.

These results in general suggests that the existence of transaction costs at least partially prevents the investors from exploiting the PEAD anomaly at full potential and that "the highest amounts of money left on the table are for firms where the money machine is most costly to access" (Scott 2015). These findings further relate to the work on informationally efficient market by Grossman and Stiglitz (1980), Fama (1991) and Jensen (1978), as it is suggested by them that rational investors are willing to arbitrage the market anomalies away only to the extent where the marginal costs do not exceed the marginal benefits. This leads to the conclusion that, in the presence of transaction costs, the PEAD anomaly is here to stay. Whether there are real-life profits to be made by exploiting such an arbitrage strategy is, however, still an alluring question for the practitioners to verge on.

3. Hypothesis development

Based on the previous research information vastly described in section 2, as well as on the persistence of the anomaly among different samples in different time periods, there is no reason to assume that PEAD would not be present also in this particular sample and in this particular time. The first hypothesis of this study is thus constructed as follows:

H1: Statistically significant PEAD does exist in the European stock markets in 2018

To prove the statistical significance of the anomaly, the significance of the average abnormal returns (AARs) as well as the significance of the cumulative average abnormal returns (CAARs) is tested with Adjusted Patell Z-test. The methodology for significance testing is further described in section *4.1.3*.

According to Garfinkel & Sokobin (2006), a common result ducumented in prior work regarding PEAD is that the anomaly is concentrated among smaller firms, implying potential selection bias concerns in tests requiring data typically available only for larger firms. Indeed, already Foster et al. (1984) have concluded that the absolute magnitude of PEAD is inversely related to firm size. Complementing this view with international evidence, Barber et al. (2013) found the PEAD to be more pronounced for the smallest stocks. In addition, the work by Bhushan (1994) showed that the concentration of PEAD among these smaller firms is likely associated with the difficulty they present in trading to take advantage of the mispricing, as the transaction costs are higher for smaller firms driving the sensitivity of PEAD to firm size. Moreover, Doyle et al. (2006) found that when the PEAD is measured based on the AF surprise, the large and persistent abnormal returns are not concentrated in a few industries and that firms with extreme earnings surprise are generally smaller than the average firm.

According to this prior information, the second and third hypothesis for this study are as follows:

H2a: Firm size is inversely related to the magnitude of PEAD

H2b: Firm size is inversely related to the length of PEAD

H3a: The economic sector has no effect on the magnitude of PEAD

H3b: The economic sector has no effect on the length of PEAD

The magnitude of PEAD refers to the amount the realized cumulative returns differ from the expected cumulative returns, i.e. to the intrinsic value of the cumulative abnormal returns (CAR). The length of PEAD refers to the count of the consecutive days from the event date onwards that the abnormal returns stay positive or negative. Detailed information regarding these definitions shall be found in section *4.2.*

4. Empirical methods

The empirical part of this study is divided in two based on the two distinct research questions. This chapter aims to describe the harnessed empirical methods (event study and OLS regression) to create a firm ground for the subsequent analyses. The reader is walked through the timeline of the event study, the determination of the abnormal returns, the deployment of the significance test as well as the models and variables regarding the regression analysis.

4.1. Event study

The event study methodology is a widely used procedure in finance and economics, developed to measure the impact of a specific event on asset price behavior and on the value of a firm (MacKinlay 1997). Binder (1998) notes that the methodology is often attributed to Fama, Fisher, Jensen and Roll (1969), who examined the effect of stock splits on the subsequent stock returns using this method. He adds that since then, the event study methodology has been widely used to examine asset price behavior around events such as mergers and acquisitions, issues of new debt or equity, accounting rule changes, changes in the severity of regulation and publishing of earnings announcements. Put simply, it has become the standard in measuring asset price reactions to an announcement or event (Binder 1998).

An event study in general can be viewed as a three-step process. First, the applicable timeframe for the study needs to be determined. This includes defining the lengths of the estimation window and event window as well as specifying the actual event date. In addition, a post-event window can be determined for additional analysis.

Second, as the abnormal returns during the event window are often the main focus in event studies, the underlying benchmark model for normal (expected) returns is to be determined. Brown and Warner (1980) note that the abnormal returns are always viewed as abnormal relative to a certain benchmark, so the determination of the underlying normal return model has a straight impact on the subsequent abnormal returns. Moreover, in sample studies such as this, the average and cumulative measures of abnormal returns are often further calculated to catch a glimpse on the trends the sample is generating.

Third, the significance of the abnormal returns needs to be tested to separate the abnormal returns generated by chance from the abnormal returns generated by the event (i.e. earnings announcement) in question. These three aspects of the event study process are further viewed and described in the following sections.

4.1.1. Estimation and event windows

Chart 1a. General timeline for an event study

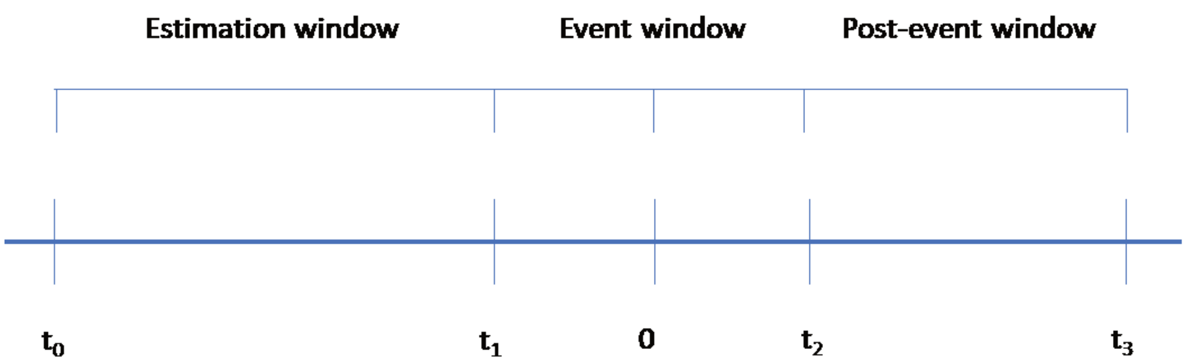


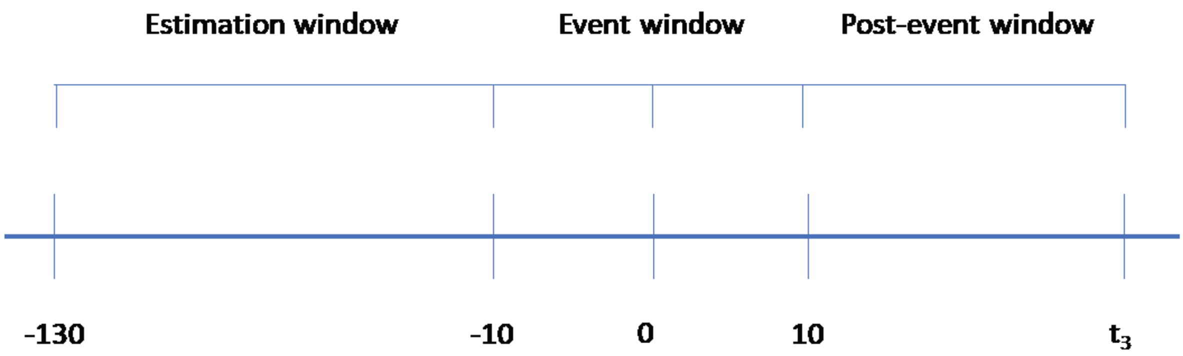
Chart 1a represents a general timeline for an event study. The area between t_0 and t_1 is called the estimation window, during which a particular model is used to determine the normal (expected) returns for a stock in question. The area between t_1 and t_0 is the event window, during which the actual occurred returns are compared to the normal returns derived from the estimation window to determine the abnormal returns, Day 0 being the actual event date. The area between t_2 and t_3 is the post-event window, which is mostly used in long-term event studies but is of no interest regarding this particular study.

First, McKinlay (1997) points out that there is no single rule on the length of the estimation and event windows. The most common way is to use the period prior to the event window for the estimation window and generally, the event window itself is excluded from the estimation window to prevent the event from affecting the normal performance model parameter estimates (MacKinlay 1997). The challenge to solve in determining the length of the estimation window is to find balance in the tradeoff between improved estimation accuracy and potential parameter shifts. Longer estimation windows improve accuracy, as they imply larger samples of returns, but they also bear the risk of covering structural breaks (e.g. due to confounding events) of the α and β factors, which will then lead to biased estimators. (Eventstudytools 2018a). However, Armitage (1995) and more recently Park (2004) found that the results are not sensitive to varying estimation window lenghts as long as the length of the estimation window exceeds 100 days.

With the event window, there exists a similar challenge as it needs to be specified over which period the studied event will have an impact on the respective stock. On one hand, information leakage and longer information processing periods favor longer event windows, and on the other hand, confounding events suggest shorter event windows. (Eventstudytools 2018a). Scott (2015) further points out that there exists a determination issue between causation and association regarding the narrow and wide window event studies. Keeping the event window narrow, it can be argued that the market reaction is caused by the accounting information released. For wide window studies, the most that can be argued is that the earnings and returns are associated. This is because much of the information in earnings releases is already built into stock prices by the time the earnings are announced, as the earnings announcements are not the only source of information for investors. (Scott 2015). In their original study, Ball and Brown (1968) estimated that so much as 85 - 90% of the earnings information was indeed already absorbed into the stock prices at the time the current earnings were announced. Nevertheless, Scott (2015) adds, the important point hereby is that the markets are unable to anticipate *all* the information in earnings releases, which underlines the usefulness of the narrow window studies.

Leaning on the arguments above, the length of the event window for this study is chosen to be 20 days, centering symmetrically to the event date. This (rather short) window is justified to prevent the event window from including confounding events but at the same time allowing it to capture the effects of an earnings announcement on stock behaviour in more than just a few days. Furthermore, the length of the estimation window for this study is chosen to be 120 days, ending to day -11 (one day before the starting of the event window) relative to the event date. By doing so, the arguments of Armitage (1995) and Park (2004) described above are also taken into consideration. As a result, the timeline for this study is as follows:

Chart 1b. Timeline for this event study



The days determined are expressed relative to the event date, while t_3 remains unspecified as it was noted that the post-event window is of no interest regarding this particular study.

4.1.2. Normal and abnormal returns

As mentioned, the appraisal of the event's impact requires measuring the abnormal returns in the event window. Abnormal returns in event studies are defined as the actual returns of the security over the event window minus the normal (expected) returns of the firm over the event window (MacKinlay 1997):

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{3}$$

where

$AR_{i,t}$ = abnormal return for stock *i* in time period *t*

$R_{i,t}$ = actual return for stock *i* in time period *t*

$E(R_{i,t})$ = normal (expected) return for stock *i* in time period *t*

As a security's price performance can only be considered abnormal relative to a particular benchmark, it is necessary to first specify a model generating the normal (expected) returns for the specific security in question (Brown & Warner 1980). The normal return is defined as the expected return without conditioning on the event taking place (MacKinlay 1997) and there are several ways to determine it. Following the categorization and examples of Brown and Warner (1980), Binder (1998) and Eventstudytools (2018a), hereby presented are the three most general models used in generating the *ex ante* normal (expected) returns:

Mean Adjusted model

The Mean Adjusted model assumes that the normal return for a stock *i* in period *t* is equal to the average return of that stock during the estimation window:

$$E(R_{i,t}) = \hat{R}_i \tag{4}$$

where

$\hat{R}_i$ = the average return of stock *i* during the estimation window

The abnormal return for stock *i* in time period *t* is subsequently determined as the actual return for the stock in time period *t* minus the average return of that stock during the estimation window:

$$AR_{i,t} = R_{i,t} - \hat{R}_i \tag{5}$$

Under this model, the length of the estimation window will obviously have an impact on the magnitude of the observed abnormal returns, because the average of the returns may very well change as the length of the estimation window varies. In addition, Binder (1998) notes that this method does not explicitly control for the risk of the stock or the return on the market portfolio. However, he adds, it might be slighlty simpler than the other models presented because only one parameter is to be estimated and no market returns are needed in the model. Under the assumption that a security has constant systematic risk and that the efficient frontier is stationary, this model is also consistent with the Capital Asset Pricing Model (Brown & Warner 1980).

Market Adjusted model

Market Adjusted model assumes that the normal return for stock *i* in period *t* equals the reference market return in period *t*:

$$E(R_{i,t}) = R_{m,t} \tag{6}$$

where

$R_{m,t}$ = the actual reference market return in time period *t*

The abnormal return for stock *i* in time period *t* is subsequently determined as the actual return for the stock in time period *t* minus the reference market return in time period *t*:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{7}$$

When the Market Adjusted model is used, no parameters need to be estimated and only the reference market return determines the abnormal component in a particular stock's return in time period *t* (Binder 1998). Using the actual market return is maybe the simplest way to control for potential effects of the event on the general market, however the model does not adjust for basic CAPM risk and thus abstracts from the firm's distinct systematic risk profile (Eventstudytools 2018a). Brown and Warner (1980) further point out that the model implicitly assumes that the normal (expected) return is equal across all securities, as long as the time period *t* is constant and the reference market is equal. They continue that if all securities have systematic risk of unity, this model is consistent with the Capital Asset Pricing Model.

Furthermore, modifications to the Market Adjusted model are also possible: Instead of referring to the market returns, researchers may as well turn to the performance of a comparable firm's stock when seeking a proxy for a distinct firm's normal returns. Thereby, one replaces the market return from the above equation with the returns of a comparable firm's stock. (Eventstudytools 2018a).

Market model

The Market model, in turn, builds on the actual returns of a reference market and the correlation of the firm's stock with the reference market. In the market model, it is assumed that the normal (expected) returns follow a single factor market model including two inputs: the typical relationship between the firm's stock and its reference index (expressed by α and β parameters) and the actual reference market return ($R_{m,t}$). The normal (expected) returns are subsequently determined as follows:

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{8}$$

where

α_i = intercept term

β_i = regression coefficient (beta), a measure of the sensitivity of $R_{i,t}$ on the reference market

$\varepsilon_{i,t}$ = error term with $E(\varepsilon_{i,t}) = 0$ and finite variance, uncorrelated to the market return $R_{m,t}$ and firm return $R_{j,t}$ with $i \neq j$, not autocorrelated and homoskedastic

The abnormal return for stock *i* in time period *t* is subsequently determined as the difference between the actual stock return in time period *t* and the normal return:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}) \tag{9}$$

Binder (1998) notes that the market model approach is quite straight-forward and relatively easy to use, as the parameters are estimated using a pre-event period sample with OLS regressions. The parameter estimates and the event period stock and market index returns are subsequently used to estimate the abnormal returns. This method also controls for the risk (via the market factor beta) of the stock and the movement of the market during the event period. (Binder 1998).

Considering the usage of these three different models in determining the normal (expected) returns, the Market model is found to be the most common practice. Of a sample of 400 event studies, 3.3% were found to draw on the Mean Adjusted model, 13.3% used the Market Adjusted model and a majority of 79.1% deployed the Market model. (Eventstudytools 2018a, see Holler 2014). In addition to these three main models, there are also several other models used in determining the normal (expected) returns. These models include the Market model with Scholes-Williams beta estimation, Market model with GARCH and EGARCH error estimations, CAPM model, Fama-French 3-factor model and Fama-French Momentum 4-factor model (Eventstudytools 2018a). Addressing these further models in detail is however beyond the scope of this study.

In this study, the Market model is utilized to determine the normal (expected) returns because it is widely accepted as the standard model, is relatively easy to use and is able to account for systematic risk via the beta factor. It is however not completely free from criticism, as it for example assumes that the risk-free interest rate included in the α factor is constant, which in turn conflicts with the presumption that market returns vary over time (Eventstudytools 2018a). As the Market model requires market returns ($R_{m,t}$) for calculating the normal (expected) returns for stock *i*, STOXX Europe 600 is chosen as the reference market index for this study. With a fixed number of 600 components, it represents large, mid and small capitalization companies across 17 countries of the European region including companies for example from France, Germany, Sweden, Finland, Netherlands and Spain (Stoxx 2018).

Average and cumulative abnormal measures

Furthermore, an analysis performed for multiple events of the same event type (such as this study) may yield typical stock market response patterns regarding the event type in question (Eventstudytools 2018b). To broaden the view outside the abnormal returns of a single stock on a single day in the event window, it is useful to introduce the concepts of cumulative abnormal returns (CARs), average abnormal returns (AARs) and cumulative average abnormal returns (CAARs).

Average abnormal returns are calculated from the sample as follows:

$$AAR = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{10}$$

By calculating the average abnormal returns, it can be concluded how the sample stocks on average behave on a single day in the event window. To measure the total impact of an event over the event window, individual abnormal returns can be added up to create cumulative abnormal returns:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{11}$$

By calculating the cumulative abnormal returns, conclusions can be made of how a single stock behaves between different time points in the event window. In a sample event study that holds multiple observations of individual event types (e.g. earnings announcements), cumulative average abnormal returns (CAARs) can be further calculated. They represent the mean values of identical events:

$$CAAR = \frac{1}{n}\sum_{i=1}^{n} CAR\,(t_1,t_2) \tag{12}$$

By calculating the cumulative average abnormal returns, the average behavior of the sample stocks between different time points in the event window is clarified. In sum, the abnormal returns (ARs) as well as the cumulative abnormal returns (CARs) are useful in determining how the returns of a single stock behave in the event window, whereas the average abnormal returns (AARs) and the cumulative average abnormal returns (CAARs) are of more use in specifying how the returns of all the sample stocks on average behave.

4.1.3. Significance testing

To test the significance of the AARs and CAARs, this study takes advantage of the Adjusted Patell Z -test, which is a parametric statistical test developed by Kolari & Pynnönen (2010). Their determination of the test statistic relies on the original Patell Z-test (also referred to as the Standardized Residual Test), first introduced by Patell (1976). The basic logic behind the original Patell Z-test is to first standardize the firm-specific abnormal returns with forecast-error corrected standard deviation:

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_{i,t}}} \tag{13}$$

where

$SAR_{i,t}$ = standardized abnormal returns for firm *i* in time period *t*

$AR_{i,t}$ = abnormal returns for firm *i* in time period *t*

$S_{AR_{i,t}}$ = forecast-error corrected standard deviation of $AR_{i,t}$

The test statistic for testing H_0: *AAR = 0* is subsequently calculated as:

$$Z_{Patell,t} = \frac{ASAR_t}{S_{ASAR_t}} \tag{14}$$

where

$ASAR_t$ = the sum over the sample of the standardized abnormal returns, $\sum_{i=1}^{N} SAR_{i,t}$

S_{ASAR_t} = the forecast-error corrected standard deviation of $ASAR_t$

To further test the significance of the cumulative average abnormal returns, the test statistic for H_0: *CAAR = 0* is obtained as:

$$Z_{Patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{CSAR_i}{S_{CSAR_i}} \tag{15}$$

where

$CSAR_i =$ the cumulative standardized abnormal returns, $CSAR_i = \sum_{t=T_1+1}^{T_2} SAR_{i,t}$

$S_{CSAR_i} =$ the forecast-error corrected standard deviation for $CSAR_i$

Regarding the flaws of the original Patell Z-test, Kolari and Pynnönen (2010) point out that event studies in general are often subject to cross-sectional correlation among abnormal returns, especially when the sample firms have the same event date. Because of this, the test statistic used to measure the significance of abnormal returns cannot implicitly assume that the abnormal returns are independent. The authors found out that even when the cross-correlation among the abnormal returns is low, the clustering event dates lead to a serious possibility of over-rejecting the null hypothesis of zero AARs when it is true. (Kolari & Pynnönen 2010).

Because of the described possibility with the original Patell Z-test to view the abnormal returns as statistically significant even though they are not, Kolari & Pynnönen (2010) suggest an improved test statistic taking into account the cross-correlation of abnormal returns as well as their inflation of event date variance. They also point out that the developed test statistic is the only parametric method that robustly corrects the clustering issues and that the test statistic further dominates nonparametric tests when testing CARs. This method is referred to as the Adjusted Patell Z-test, and is utilized in this study to avoid the over-rejection of $H_0: AAR = CAAR = 0$ caused by the possible cross-correlation of the abnormal returns.

The test statistic for $H_0: AAR = 0$ for the Adjusted Patell Z-test is defined as follows:

$$Z_{AdjPatell,t} = Z_{Patell,t} \sqrt{\frac{1}{1+(N-1)\bar{r}}} \tag{16}$$

where

$Z_{Patell,t}$ = the original Patell test statistic

$\bar{r}$ = the average of the sample cross-correlation of the estimation period abnormal returns

It is observable from the above equation that if $\bar{r}$ equals zero, the adjusted test statistic equals the original Patell test statistic. Otherwise, a correction takes place. As the original Patell test statistic, also the Adjusted Patell test statistic can be used to measure the significance of the cumulative average abnormal returns. The test statistic for H_0*: CAAR = 0* is obtained as:

$$Z_{AdjPatell} = Z_{Patell}\sqrt{\frac{1}{1+(N-1)\bar{r}}} \qquad (17)$$

4.2. OLS regression

4.2.1. Model 1

The firm-specific intrinsic values of the CARs as well as the lengths of the drift from the event date onwards, both obtained from the event study phase, are further explained with ordinary least squares (OLS) regression analysis. The effect of company's size on the dependent variables is measured with one independent variable, while the effect of the industry sector on the dependent variables is measured with ten dummy variables. The regression analysis is conducted to answer the main research question (*Question 2*).

The first and a general regression model (*Model 1*) is constructed as follows:

$$\left|CAR(t_1, t_2)_i\right| = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \qquad (18)$$

where

$\left| CAR(t_1, t_2)_i \right|$ $=$ intrinsic value of the cumulative abnormal returns for firm *i*'s stock from t_1 to t_2

β_0 $=$ intercept term

$logMarketCap_i$ $=$ natural logarithm of the market capitalization of the firm *i* at 31.12.2017. A logarithmic transformation is conducted to assume a linear relationship in the model.

IT_i, $ConsumerDiscretionary_i$, $HealthCare_i$, $Financials_i$, $CommunicationServices_i$, $Materials_i$, $RealEstate_i$, $ConsumerStaples_i$, $Utilities_i$ and $Energy_i$ $=$ binary dummy variables

ε_i $=$ general error term with $E(\varepsilon) = 0$

The dummy variables in the model are based on the GICS Economic Sector classification. The Industrials sector (being the most representative single sector) is left out of the model as the reference category to avoid the dummy variable trap. Hence, the intercept β_0 will capture the effect of Industrials sector in the model and the coefficient estimate for a particular dummy variable will tell the difference relative to the Industrials sector.

The dummy variables in the model are binary, so they get either one of the values 0 and 1 depending on the sector. For example, if firm *i* operates in the financial sector, the variable $Financials_i$ gets a value of 1 while all of the other dummy variables get a value of 0, as by definiton one firm cannot operate in two sectors at the same time.

Intrinsic values of the CARs are used in this study because the cumulative abnormal returns' absolute deviation from zero (the magnitude) is of interest hereby, not so much the sign of the CARs. Further determining the time points t_1 and t_2 leads from the general model (*Model 1*) to specified models *1a, 1b* and *1c,* so that for all of these models the independent variables remain as determined but for *Model 1a*: $t_1 = 1$, $t_2 = 2$ → Dependent variable $= \left| CAR(1, 2)_i \right|$

for *Model 1b*: $t_1 = 1$, $t_2 = 5$ → Dependent variable $= \left| CAR(1, 5)_i \right|$

for *Model 1c*: $t_1 = 1$, $t_2 = 10$ → Dependent variable $= \left| CAR(1, 10)_i \right|$

These three specified models are constructed to catch a glimpse on how the independent variables affect the CARs between different time points, i.e. how firm size and economic sector relate to the two-day drift, five-day drift and ten-day drift. The event date is in all of the models *1a*, *1b* and *1c* excluded from the timeframe, as the focus is especially in explaining the drift (defined as what happens *after* the event date) rather than in explaining the abnormal returns on the event date.

4.2.2. Model 2

Model 2 deviates from *Model 1* in the sense that the length of the drift in days from the event date onwards is of interest, rather than the magnitude of the cumulative abnormal returns. This model is constructed to find out whether the independent variables have an effect on the length rather than on the magnitude of the drift.

Model 2 is subsequently constructed as follows:

$$L_i = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \tag{19}$$

where

L_i = Length of the drift for firm *i*, measured in days from the event date onwards so that

if $AR_{i,0} \geq 0,\ AR_{i,1} < 0$ or if $AR_{i,0} < 0,\ AR_{i,1} \geq 0$, then $L_i = 0$

if $AR_{i,0} \geq 0,\ AR_{i,1} \geq 0$ or if $AR_{i,0} < 0,\ AR_{i,1} < 0$, then $L_i = 1$

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, then $L_i = 2$

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$, $AR_{i,3} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, $AR_{i,3} < 0$, then $L_i = 3$

. . .

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$, $AR_{i,3} \geq 0$, $AR_{i,4} \geq 0$, $AR_{i,5} \geq 0$, $AR_{i,6} \geq 0$, $AR_{i,7} \geq 0$, $AR_{i,8} \geq 0$, $AR_{i,9} \geq 0$, $AR_{i,10} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, $AR_{i,3} < 0$, $AR_{i,4} < 0$, $AR_{i,5} < 0$, $AR_{i,6} < 0$, $AR_{i,7} < 0$, $AR_{i,8} < 0$, $AR_{i,9} < 0$, $AR_{i,10} < 0$, then $L_i = 10$

, $L_i = 0, 1, 2, 3, \dots, 10$.

The other variables in *Model 2* are defined as in *Model 1*.

As a summary of the deployed methodology, the event study is conducted first to find out the abnormal returns (ARs) for the individual sample stocks in the event window, based on which the firm-specific drift lenghts are calculated. Further, the cumulative abnormal returns (CARs) as well as the average abnormal returns (AARs) and the cumulative average abnormal returns (CAARs) in the event window are calculated based on the individual abnormal returns (ARs).

Second, the significance of the AARs and CAARs between different time points is examined in order to find answers for the first research question. In addition, the firm-specific CARs and drift lengths are explained with the four different regression models described above to find answers for the second research question.

5. Data

In this chapter, the data for this study is further reviewed. This includes specifying how the sample for this study was selected as well as clarifying the qualities of the sample in the form of descriptive statistics.

5.1. Sample selection

The data for this study was gathered from Thomson Reuters Datastream. Initially, all European and Russian companies excluding UK companies who had published their latest financial statement between 1.1.2018 – 30.9.2018 were considered. The companies from the UK were excluded from this study as they have gained attention from previous PEAD studies and one of the missions of this study was to explore the areas where PEAD has not been researched to such a great extent. Creating a subsample like this allowed the exploration of the previously unresearched markets more efficiently. Second, the research regarding PEAD is generally quite well up to date, so in order to maximize the value of contribution, this study focused on the most recent publications of financial statement information. Thus, the time period during which the latest financial statement had to be published was required to be 1.1.2018 – 30.9.2018.

Third, the sample companies were further required to have market capitalization at year end 2017 (31.12.2017) available. The date was specified as is because the market capitalizations at that time were not yet affected by the financial statement information released between 1.1.2018 – 30.9.2018. This makes the market capitalizations among the sample firms comparable in the sense that the information content released in 2018 cannot have for any firm's part affected the market capitalization at year end 2017.

Fourth, the sample companies were required to have the CIGS Economic Sector classification available. As a result, Datastream was able to provide data from 2219 companies in Europe (including Russia and excluding the UK).

Table 1. Excluded firms

Firms imported from Datastream		2219
Reason for deleting	**Deleted**	**Sum after deleting**
Earnings surprise percentage missing	209	2010
Total assets missing	11	1999
Revenue 0 or missing	29	1970
Imperfect stock data between 5.6.2017 - 12.10.2018	85	1885
Extreme positive earnings surprise (1%)	19	1866
Extreme negative earnings surprise (1%)	19	1847

The data imported from Datastream consisted of 2219 firms that met the four initial requirements described above. After this, the data was further reviewed to remove the blanks and inconsistencies from it. As *Table 1* shows, there were 209 firms who had a missing value for earnings surprise percentage, measured as the relative surprise between the reported earnings in the latest financial statement and the average of all analysts forecasts. Earnings surprise percentage was required in order to divide the final sample into firms who had in their lates financial statement reported good news (GN) and bad news (BN) in relation to what was expected.

In addition, there were 11 firms in the sample who had a missing value for total assets and 29 firms whose revenue was zero or missing. Total assets and revenue (both as reported in the latest financial statement) were required variables in order to perform a sensitivity analysis with size variables other than market capitalization. Furthermore, there were 85 firms that did not have perfect stock data available between 5.6.2017 – 12.10.2018. Perfect stock data for that time period was required in order to meet the lenghts of the estimation and event windows.

FInally, the data was classified based on the magnitude of the earnings surprise percentage and 1% of both ends was deleted to preserve the final data from outlier effects. In sum, this procedure resulted in 38 firms being deleted from the sample. Consequently, the final sample consists of 1847 firms with the following features.

5.2. Descriptive statistics

Table 2. Sample divided based on the country of exchange

Country of exchange	# of firms	% of total sample	Cumulative #	Cumulative %
France	335	18.1 %	335	18.1 %
Germany	299	16.2 %	634	34.3 %
Sweden	294	15.9 %	928	50.2 %
Italy	163	8.8 %	1091	59.1 %
Switzerland	128	6.9 %	1219	66.0 %
Norway	114	6.2 %	1333	72.2 %
Finland	104	5.6 %	1437	77.8 %
Spain	80	4.3 %	1517	82.1 %
Netherlands	79	4.3 %	1596	86.4 %
Poland	71	3.8 %	1667	90.3 %
Belgium	58	3.1 %	1725	93.4 %
Denmark	44	2.4 %	1769	95.8 %
Greece	27	1.5 %	1796	97.2 %
Russia	24	1.3 %	1820	98.5 %
Estonia	9	0.5 %	1829	99.0 %
Hungary	6	0.3 %	1835	99.4 %
Romania	6	0.3 %	1841	99.7 %
Lithuania	5	0.3 %	1846	99.9 %
Latvia	1	0.1 %	1847	100.0 %
	1847	100.0 %		

Table 2 presents the final sample classified based on the firm's country of exchange. In sum, there are firms from 19 different countries included in the sample, the three most representative countries in this sense being France, Germany and Sweden, respectively. The firms from these three countries consist around a half of the total sample, as the ten most representative countries consist a little over 90% of the total sample.

Table 3. Sample divided based on the CIGS Economic Sector

Economic Sector	No. of firms	% of total sample	Cumulative No.	Cumulative %
Industrials	392	21.2 %	392	21.2 %
Information Technology	235	12.7 %	627	33.9 %
Consumer Discretionary	214	11.6 %	841	45.5 %
Health Care	211	11.4 %	1052	57.0 %
Financials	204	11.0 %	1256	68.0 %
Communication Services	126	6.8 %	1382	74.8 %
Materials	118	6.4 %	1500	81.2 %
Real Estate	113	6.1 %	1613	87.3 %
Consumer Staples	99	5.4 %	1712	92.7 %
Energy	84	4.5 %	1796	97.2 %
Utilities	51	2.8 %	1847	100.0 %
	1847	100.0 %		

Table 3, in turn, represents the final sample classified based on the GICS Economic sector. Altogether there are 11 different sectors represented in the sample, the Industrials sector being the largest single sector constituting around one fifth of the total sample. In addition, the firms from the four most representative sectors (Industrials, IT, Consumer Discretionary and Health Care) form well over 50% of the total sample.

Table 4. Good news and bad news stocks divided based on country of exchange and GICS economic sector

Country of ex.	*GN*	*%*	*BN*	*%*	**Economic Sector**	*GN*	*%*	*BN*	*%*
France	152	45.4 %	183	54.6 %	Industrials	187	47.7 %	205	52.3 %
Germany	128	42.8 %	171	57.2 %	IT	101	43.0 %	134	57.0 %
Sweden	152	51.7 %	142	48.3 %	Cons. Disc.	87	40.7 %	127	59.3 %
Italy	76	46.6 %	87	53.4 %	Health Care	86	40.8 %	125	59.2 %
Switzerland	62	48.4 %	66	51.6 %	Financials	108	52.9 %	96	47.1 %
Norway	48	42.1 %	66	57.9 %	Comm. Services	54	42.9 %	72	57.1 %
Finland	41	39.4 %	63	60.6 %	Materials	56	47.5 %	62	52.5 %
Spain	32	40.0 %	48	60.0 %	Real Estate	58	51.3 %	55	48.7 %
Netherlands	36	45.6 %	43	54.4 %	Cons. Staples	50	50.5 %	49	49.5 %
Poland	33	46.5 %	38	53.5 %	Energy	38	45.2 %	46	54.8 %
Belgium	24	41.4 %	34	58.6 %	Utilities	26	51.0 %	25	49.0 %
Denmark	23	52.3 %	21	47.7 %					
Greece	14	51.9 %	13	48.1 %					
Russia	11	45.8 %	13	54.2 %					
Estonia	4	44.4 %	5	55.6 %					
Hungary	5	83.3 %	1	16.7 %					
Romania	5	83.3 %	1	16.7 %					
Lithuania	4	80.0 %	1	20.0 %					
Latvia	1	100.0 %	0	0.0 %					
	851		996			851		996	

Table 4 further examines the polarization of the sample stocks into GN (good news) and BN (bad news) categories based on the country of exchange and the CIGS Economic Sector classification. A stock is considered as a GN stock if the corresponding earnings surprise obtained from Datastream is 0.00% or greater. Similarly, a stock is considered as a BN stock if the earnings surprise is less than 0.00%. Altogether, this classification results in 851 and 996 firms forming the GN and BN groups, respectively.

Regardless of the grouping variable (country or sector), the firms in the sample seem to be quite equally distributed into GN and BN categories. If the four most unrepresentative countries are left out of the scope, the most unequal distribution among country classification can be found among Finnish stocks, of which 60.6% are BN stocks and 39.4% GN stocks. Considering the classification based on economic sector, the most unequal distribution can be found in Consumer Discretionary sector where 59.3% of the stocks are

BN stocks and 40.7% are GN stocks. This classification verifies that no single country or sector is overrepresented in either of the BN/GN categories.

Table 5. Sector-specific descriptive statistics for Market Cap (in millions of €)

Economic sector	**Median MC**	**Mean MC**	**Largest MC**	**Smallest MC**
Utilities	2,617.93	7,484.70	52,155.07	41.77
Financials	2,274.99	8,486.05	88,409.99	40.73
Materials	1,304.05	5,491.42	84,261.24	1.09
Consumer Staples	1,109.37	10,664.90	223,139.34	8.19
Communication Services	853.80	4,260.29	70,445.78	6.07
Real Estate	831.25	2,058.09	20,967.05	13.14
Industrials	785.17	3,456.83	64,288.15	1.74
Energy	720.01	10,033.76	233,560.89	3.06
Consumer Discretionary	561.80	5,205.98	124,416.19	8.47
Health Care	298.72	4,809.17	183,717.98	2.87
IT	240.74	1,990.45	114,803.72	2.98
Total sample	666.90	5,078.79	233,560.89	1.09

Finally, *Table 5* provides sector-specific descriptive statistics for market capitalization (illustrated in millions of €). These statistics help in gaining sight on how the size variable may work through the sector variables in the OLS regression models. If the companies in one sector were found to be on average significantly larger (or smaller) than the companies in the Industrials (reference) sector and the particular sector dummy was subsequently found significant, it would have to be noted that it is the size that causes the possible significance of the dummy variable and not the economic sector itself. This table is consequently further referred to during the analysis of the regression outputs.

6. Empirical findings

This chapter dives into the empirical findings of this study. First, the overall results of the event study analysis as well as the results of the OLS regression analysis are reviewed. Second, a summary of the results is provided in the end of this chapter along with discussion and limitations.

6.1. Event study

The final sample for the event study analysis consisted of 996 bad news stocks and 850 good news stocks, as one stock from the BN category was left out due to the reason that the prices (and consequently the returns) of that stock were constant in the estimation window (data error in Datastream). To gain a complete understanding of the results, a visual illustration of the cumulative average abnormal returns (CAARs) in the event window is presented first. Second, further tables concluding the significance tests for the average abnormal returns (AARs) and for the cumulative average abnormal returns (CAARs) are provided.

Chart 2. Cumulative average abnormal returns in the event window

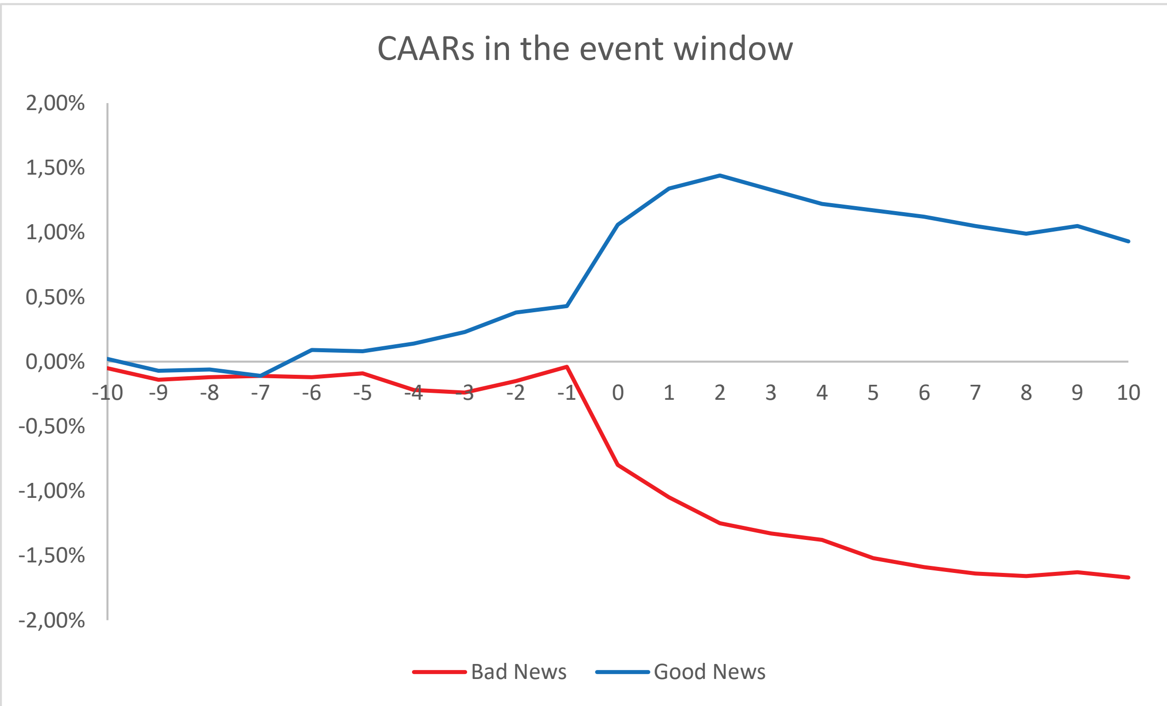


Table 6. Average abnormal returns, cumulative average abnormal returns and the significance test for average abnormal returns

	Good News				Bad News			
Day	*AAR*	*Adj. Pat. Z*	*Sig. of AAR*	*CAAR*	*AAR*	*Adj. Pat. Z*	*Sig. of AAR*	*CAAR*
-10	0.02 %	-0.169		0.02 %	-0.05 %	0.132		-0.05 %
-9	-0.09 %	-0.831		-0.07 %	-0.09 %	-1.383		-0.14 %
-8	0.01 %	-0.248		-0.06 %	0.02 %	0.151		-0.12 %
-7	-0.05 %	-0.469		-0.11 %	0.01 %	-0.558		-0.11 %
-6	0.20 %	2.993	**	0.09 %	-0.01 %	1.256		-0.12 %
-5	-0.01 %	-0.049		0.08 %	0.03 %	1.246		-0.09 %
-4	0.06 %	0.785		0.14 %	-0.13 %	-0.934		-0.22 %
-3	0.09 %	2.057	*	0.23 %	-0.02 %	-0.741		-0.24 %
-2	0.15 %	3.217	**	0.38 %	0.09 %	2.134	*	-0.15 %
-1	0.05 %	1.099		0.43 %	0.11 %	2.077	*	-0.04 %
0	0.63 %	12.384	**	1.06 %	-0.76 %	-15.239	**	-0.80 %
1	0.28 %	7.982	**	1.34 %	-0.25 %	-4.465	**	-1.05 %
2	0.10 %	1.958		1.44 %	-0.20 %	-2.741	**	-1.25 %
3	-0.11 %	-1.231		1.33 %	-0.08 %	-0.505		-1.33 %
4	-0.11 %	-2.489		1.22 %	-0.05 %	-1.677		-1.38 %
5	-0.05 %	-0.804		1.17 %	-0.14 %	-2.007	*	-1.52 %
6	-0.05 %	-0.320		1.12 %	-0.07 %	-1.137		-1.59 %
7	-0.07 %	-0.947		1.05 %	-0.05 %	-1.942		-1.64 %
8	-0.06 %	-1.233		0.99 %	-0.02 %	-0.228		-1.66 %
9	0.06 %	2.427	**	1.05 %	0.03 %	-0.649		-1.63 %
10	-0.12 %	-2.009	**	0.93 %	-0.04 %	-0.502		-1.67 %

* = significant at 5% significance level
** = significant at 1% significance level

Chart 2 presents the cumulative average abnormal returns in the event window for GN and BN stocks, as *Table 6* further numerically verifies the visual output of *Chart 2*. Together they provide interesting insight about the PEAD anomaly in ex-UK Europe based on financial statement information released in 2018 and suggest answers to the first research question of this study. First, it is clearly observable from *Chart 2* that published financial information does have great value relevance, as both the curves face steep shifts and statistically significant abnormal returns (at 1% significance level) on the event date. Second, the PEAD anomaly still seems to be present in the stock markets especially among the BN stocks, as the negative drift for BN stocks, on average, continues on all days subsequent to the event date except on Day 9 (+0,03% return, statistically insignificant).

However, the curve for the GN stocks tells a different story. In line with previous studies, the GN stocks do seem to experience statistically significant positive abnormal returns on the event date and on Day 1. In addition, they gain statistically insignificant positive abnormal returns on Day 2 but after that, they actually seem to have a slight *negative* drift, as the average abnormal returns continue to be negative on all days after Day 2 except for Day 9 (+0,06% return, significant at 5% significance level). This implies that the market may actually overreact to the positive earnings surprises on the event date, Day 1 and Day 2, after which a price correction takes place. Similar behavior is not observable with the BN stocks, as the ongoing negative drift among them implies an underreaction to the earnings information.

Third, it is observable from *Table 6* that both the groups experience statistically significant positive abnormal returns also before the event date. For the GN stocks, it is possible that there are press releases, analyst forecast revisions or other small pieces of new information regarding the subsequent release of financial information that have transpired on those days. According to MacKinlay (1997), the market may acquire information about the earnings prior to the actual announcement, which may be observable from the pre-event returns, as in the case of this study. Scott (2015) further points out that as the earnings announcements are not the only source of information for investors, much of the information content in the earnings releases is likely to be already built into the stock prices by the time the earnings are announced. However, as mentioned, it is clearly observable also from the results of this study that the market could not anticipate all the information and, subsequently, the released information can be concluded to have value relevance.

Further into the abnormal returns perceived before the event date, an interesting observation is that the BN stocks seem to also experience positive abnormal returns on Day -2 and -1. The positive pre-event average abnormal returns and the subsequent negative earnings surprise are not coherent with the above reasoning regarding the upfront absorbed information. With the GN stock, investors seem to have correctly anticipated the good news beforehand but with the BN stocks, they seem to have wrongly anticipated better news than actually was released and thus falsely bidden up the stock prices.

However, as this study investigates only the effects of the actual publishing of the financial statement, little can be said about the specific reasons causing the pre-announcement abnormal returns.

Table 7. Cumulative average abnormal returns and the significance tests

	Good News			**Bad News**		
CAAR type	*CAAR value*	*Adj. Pat. Z*	*Sig. of CAAR*	*CAAR value*	*Adj. Pat. Z*	*Sig. of CAAR*
(0;5)	0.73 %	7.338	**	-1.47 %	-9.138	**
(0;10)	0.49 %	4.785	**	-1.62 %	-7.878	**
(1;2)	0.38 %	7.097	**	-0.44 %	-4.282	**
(1;3)	0.27 %	5.077	**	-0.52 %	-3.741	**
(1;4)	0.16 %	3.140	**	-0.57 %	-3.944	**
(1;5)	0.10 %	2.446	*	-0.71 %	-4.282	**
(1;10)	-0.14 %	1.064		-0.86 %	-4.213	**
(2;5)	-0.18 %	-1.296		-0.46 %	-2.912	**
(2;10)	-0.42 %	-1.565		-0.61 %	-3.190	**
(-10;10)	0.91 %	5.311	**	-1.64 %	-5.082	**

** = significant at 1% significance level
* = significant at 5% significance level

As *Table 6* verified the level of significance of the AARs on a single day level, *Table 7* further examines the significance of the CAARs between different time points in the event window. Consequently, these results explain whether the drift as a whole from t_1 to t_2 is of statistical significance or not.

It is observable from the above table that among the BN stocks, the CAARs are significant at 1% significance level between all tested timepoints. Among the GN stocks, the CAARs are found to be statistically significant in all tested time periods including the event date (0;5, 0;10 and -10;10). However, when the event date is excluded and more limited time frame is tested, the CAARs among the GN stocks seem to gradually lose their significance. Moreover, when the time period tested begins as late as on Day 2, the CAARs among GN stocks are found to be insignificant. This further verifies the result that the drift among the

GN stocks centers primarily within Days 1 and 2 after which a price correction takes place, while the BN stocks experience a longer and altogether more pronounced drift.

From the practical point of view, these results together seem to suggest that a portfolio construction including a long position on the GN stocks from Day 0 to Day 2 and a short position on the BN stocks from Day 0 to Day 10 would have, on average, yielded riskless arbitrage profits. However, this statement is somewhat naïve as it does not take into account the possible transaction costs caused by i.e. constructing such a portfolio and further selling the stocks. The reader is also hereby reminded that according to Grossman and Stiglitz (1980), Jensen (1978) and Fama (1991), there must be some quantity of abnormal profits to be made in the markets to compensate the informed investors for the costs of information collection. Thus, in equilibrium, the abnormal profits gained by informed investors equal exactly the costs of collecting the information (Grossman & Stiglitz 1980) and consequently, asset prices are reflecting information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs (Jensen 1978; Fama 1991).

As the portfolio construction and the determination of applicable transaction costs are beyond the scope of this study, it is hereby only noted that abnormal profits may have been able to be acquired following a strategy similar to what was just described. However, *H1* suggesting that statistically significant PEAD does exist in the European stock markets in 2018 is hereby verified to be accurate especially when considering the BN stocks, as the AARs and CAARs among them were generally found to be of statistical significance.

6.2. OLS regression analysis

Going into the second part of the empirical findings, this section describes the results obtained with the OLS regression analyses. This includes reviewing the regression outputs of all of the four deployed regression models.

Model 1a

A described in section *4.2.1.*, *Model 1a* was further specified based on the general *Model 1* so that the intrinsic value of the cumulative abnormal return from Day 1 to Day 2 for firm *i* was chosen to be the dependent variable. This choice was made in order to explain the short-term (two-day) drift with the independent variables. It should be further noted that the model takes no view wheter a single $CAR(1;2)_i$ in the sample is statistically significant or not.

Model 1a was consequently defined as follows:

$$\left| CAR(1;2)_i \right| = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \quad (20)$$

where

$\left| CAR(1;2)_i \right|$ = the intrinsic value of the cumulative abnormal return from Day 1 to Day 2 for firm *i*

The independent variables are as described earlier in section *4.2.1.*

Table 8. Regression output – Model 1a

Variable	*Coefficient*	*Std. Error*	*t-value*	*P-value*	*Sig.*
Intercept	0.0683	0.0088	7.7842	0.0000	**
logMarketCap	-0.0019	0.0004	-4.5062	0.0000	**
IT	0.0037	0.0030	1.2632	0.2067	
ConsumerDiscretionary	-0.0013	0.0030	-0.4213	0.6736	
HealthCare	0.0057	0.0030	1.8660	0.0622	
Financials	-0.0071	0.0031	-2.3196	0.0205	*
CommunicationServices	0.0026	0.0037	0.7223	0.4702	
Materials	-0.0019	0.0037	-0.5204	0.6029	
RealEstate	-0.0101	0.0038	-2.6616	0.0078	**
ConsumerStaples	-0.0016	0.0040	-0.3962	0.6920	
Utilities	-0.0044	0.0053	-0.8346	0.4041	
Energy	0.0074	0.0042	1.7708	0.0768	

** = significant at 1% significance level
* = significant at 5% significance level

R^2 = 0.0339
Adjusted R^2 = 0.0281

Table 8 goes through the regression output of *Model 1a.* First of all, it should be noted that the R^2 and Adjusted R^2 statistics of the model are very low. This implies that *Model 1a* as a whole does not explain the observed PEAD in European stock markets very well, as there surely are also many other determinants affecting the anomaly. However, there are still further points to be drawn out from *Table 8*.

According to *H2a*, it was hypothesized that the coefficient estimate for $logMarketCap_i$ will be negative. As a prior assumption of the sign of the coefficient estimate was made, one-sided significance test was conducted with the corresponding *t*-value presented in *Table 8*. The results are consistent with what was hypothesized, as the coefficient estimate for $logMarketCap_i$ is indeed found to be negative and statistically significant at 1% significance level. This result and the corresponding coefficient estimate can be further interpreted so that as the market capitalization increases 1%, the intrinsic value of the cumulative abnormal returns from Day 1 to Day 2 is expected to decrease on average 0.000019 percentage points, ceteris paribus. A more practical comparison would be that as that the market capitalization doubles (i.e. increases 100%), the intrinsic value of CAR(1;2) is expected to be on average 0.0019 percentage points lower, ceteris paribus. Furthermore, it can be argued that if two firms, say firm *A* and firm *B,* were operating in the same economic sector and firm *A* had a market capitalization ten times that of firm *B*, firm *A* would be expected to have on average 0.0171 percentage points lower intrinsic value of CAR(1;2) than firm *B*, ceteris paribus.

Moreover, according to *H3a,* it was hypothesized that the coefficient estimates for the independent variables measuring the effect of economic sector on CAR(1;2)$_i$ will be insignificant and no prior assumption was made of the sign of these coefficient estimates (positive or negative). Therefore, a two-sided significance test is applicable and the corresponding significance level can be interpreted straight from the P-values presented in *Table 8*.

On the contrary to what was hypothesized*, Table 8* shows that the coefficient estimates for the dummy variables *Financials*$_i$ and *RealEstate$_i$* are found to be significant at 5% and 1% significance levels, respectively. The interpretation of the corresponding coefficient suggests that compared to a firm operating in Industrials sector, the intrinsic value of the cumulative abnormal returns from Day 1 to Day 2 are expected to be on average (ceteris paribus) 0.0071 and 0.010 percentage points lower for a firm that operates in Financials and Real Estate sector, respectively.

Model 1b

Model 1b was as well constructed based on the general *Model 1* so that the intrinsic values of cumulative abnormal returns from Day 1 to Day 5 were chosen to be the dependent variables. This choice was made to assess a longer (five-day) drift than with *Model 1a* to see if the relation between the independent and dependent variables changes with the length of the time period. Neither this model takes a view on whether a single CAR(1;5)$_i$ in the sample is statistically significant or not.

Model 1b was subsequently defined as follows:

$$|CAR(1;5)_i| = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \quad (21)$$

where

$|CAR(1;5)_i|$ = the intrinsic value of the cumulative abnormal return from Day 1 to Day 5 for firm *i*

The independent variables are again as described earlier in section *4.2.1.*

Table 9. Regression output – Model 1b

Variable	*Coefficient*	*Std. Error*	*t-value*	*P-value*	*Sig.*
Intercept	0.0986	0.0107	9.2307	0.0000	**
logMarketCap	-0.0029	0.0005	-5.6532	0.0000	**
IT	0.0011	0.0036	0.3096	0.7569	
ConsumerDiscretionary	0.0004	0.0037	0.1108	0.9118	
HealthCare	0.0110	0.0037	2.9748	0.0030	**
Financials	-0.0086	0.0037	-2.2986	0.0216	*
CommunicationServices	0.0045	0.0044	1.0180	0.3088	
Materials	-0.0026	0.0045	-0.5705	0.5684	
RealEstate	-0.0165	0.0046	-3.5765	0.0004	**
ConsumerStaples	0.0008	0.0049	0.1666	0.8677	
Utilities	-0.0048	0.0065	-0.7454	0.4561	
Energy	0.0135	0.0051	2.6350	0.0085	**

** = significant at 1% significance level
*   = significant at 5% significance level

R^2 = 0.0499
Adjusted R^2 = 0.0442

The regression output of *Model 1b* is presented in *Table 9.* Again, the R^2 and Adjsuted R^2 statistics remain low but are still somewhat higher compared to the ones obtained with *Model 1a*. This implies that the right-hand side of the *Model 1* is slighty more relevant in explaining the intrsinsic values of the CARs from Day 1 to Day 5 than the intrinsic values of the CARs from Day 1 to Day 2. Referring to *H2a*, it was again hypothesized that the coefficient estimate for $logMarketCap_i$ will be negative.

Similar to the regression output of *Model 1a*, the regression output of *Model 1b* also finds the negative association between the market capitalization and magnitude of the cumulative abnormal returns to be significant. The coefficient estimate for $logMarketCap_i$ remains negative and significant at 1% significant level with a higher *t*-value than in *Model 1a*. The corresponding coefficient estimate can be further interpreted so that as the market capitalization increases 1%, the intrinsic value of the cumulative abnormal returns from Day 1 to Day 5 is expected to decrease on average 0.000029 percentage points, ceteris paribus. Again, a more reasonable comparison would be that as the market capitalization doubles, the intrinsic value of CAR(1;5) is expected to decrease on average 0.0029 percentage points, ceteris paribus. Furthermore, firm *A* having a market capitalization ten times that of firm *B* would be expected to have 0.0261 percentage points lower intrinsic value of CAR(1;5) compared to firm *B*, ceteris paribus. Similar to the interpretation of the results of *Model 1a,* this implies in general that higher market capitalization suggests a milder deviation from the expected returns also within Day 1 and Day 5.

Referring to *H3a* as with *Model 1a,* it was again hypothesized that the coefficient estimates for the independent variables measuring the effect of economic sector on $CAR(1;5)_i$ will be insignificant and no prior assumption was made of the sign of these coefficient estimates (positive or negative). Compared to the regression output of *Model 1a*, *Table 9* shows that the coefficient estimates for $Financials_i$ and $RealEstate_i$ are again found to be significant at 5% and 1% significance levels, respectively. In addition to that, the coefficient estimates for $HealtCare_i$ and $Energy_i$ are also found to be significant at 1% significance level.

The corresponding coefficients suggest that compared to a firm operating in Industrials sector, the intrinsic value of CAR(1;5) is expected to be on average (ceteris paribus) 0.0086 and 0.0165 percentage points lower for a firm operating in Financials and Real Estate sector, respectively. Furthermore, again compared to a firm operating in Industrials sector, the intrinsic value of CAR(1;5) is expected to be on average (ceteris paribus) 0.0110 and

0.0135 percentage higher for a firm operating in Health Care and Energy sector, respectively.

Model 1c

As the models *1a* and *1b, Model 1c* was also derived from the general *Model 1* so that the intrinsic values of cumulative abnormal returns from Day 1 to Day 10 were chosen to be the dependent variables. The purpose of this model is to explain the long-term (ten-day) drift with the already familiar independent variables. As with the two previous models, neither this model takes a view on whether a single $CAR(1;10)_i$ in the sample is statistically significant or not.

Model 1c was subsequently defined as follows:

$$\left| CAR(1;10)_i \right| = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \qquad (22)$$

where

$\left| CAR(1;10)_i \right|$ = the intrinsic value of the cumulative abnormal return from Day 1 to Day 10 for firm *i*

The independent variables are again as described earlier in section *4.2.1.*

Table 10. Regression output – Model 1c

Variable	*Coefficient*	*Std. Error*	*t-value*	*P-value*	*Sig.*
Intercept	0.1175	0.0129	9.1121	0.0000	**
logMarketCap	-0.0035	0.0006	-5.5953	0.0000	**
IT	0.0063	0.0044	1.4434	0.1491	
ConsumerDiscretionary	0.0035	0.0044	0.7818	0.4344	
HealthCare	0.0213	0.0045	4.7641	0.0000	**
Financials	-0.0044	0.0045	-0.9718	0.3313	
CommunicationServices	0.0055	0.0054	1.0284	0.3039	
Materials	-0.0028	0.0055	-0.5161	0.6059	
RealEstate	-0.0179	0.0056	-3.2108	0.0013	**
ConsumerStaples	-0.0020	0.0059	-0.3386	0.7350	
Utilities	-0.0029	0.0078	-0.3736	0.7088	
Energy	0.0198	0.0062	3.2070	0.0014	**

** = significant at 1% significance level
* = significant at 5% significance level

R^2 = 0.0574
Adjusted R^2 = 0.0518

Table 10 represents the regression output for *Model 1c*. As with the two previous models, the R^2 and Adjusted R^2 statistics are again far from high, but *Model 1c* still offers the highest values of these statistics. As no further variables were at any point added to the right-hand side of the model, the comparison of the R^2 statistics of the three different models imply that the independent variables of the model can (only) slightly better explain the intrinsic values of the cumulative abnormal returns as the time period for measuring the CARs is prolonged.

Going into the significance of the coefficient estimates, the negative association between firm size and the magnitude of the cumulative abnormal returns is further emphasized with *Model 1c*. The coefficient estimate for *logMarketCap$_i$* is again found to be negative and significant at 1% significance level as with the two previous models, and the result suggests that as the market capitalization increases 1%, the intrinsic value of the cumulative abnormal returns from Day 1 to Day 10 is expected to decrease on average 0.000035 percentage points, ceteris paribus. Similar to the previous practical examples, the intrinsic value of CAR(1;10) is expected to be on average 0.0035 and 0.0315 percentage points lower for firms having market capitalization doubled or tenfolded, respectively (ceteris paribus). This result further amplifies the argument that higher market capitalization is indeed related to a milder deviation from the expected returns.

As with the two previous models, contradictory evidence to *H3a* is also provided. The coefficient estimates for the dummy variables $HealthCare_i$, $RealEstate_i$ and $Energy_i$ are found to be statistically significant, all of them at 1% significance level. The corresponding coefficients suggest that compared to a firm operating in Industrials sector, the intrinsic value of CAR(1;10) is expected to be on average (ceteris paribus) 0.0179 percentage points lower for a firm operating in Real Estate sector. In addition, again compared to a firm operating in Industrials sector, the intrinsic value of CAR(1;10) is expected to be on average (ceteris paribus) 0.0213 and 0.0198 percentage points higher for a firm operating in Health Care and Energy sector, respectively.

Model 2

Model 2 deviates from models *1a*, *1b* and *1c* in the sense that it is the length of the drift in days from the event date onwards that is of interest, rather than the magnitude of the cumulative abnormal returns. This model is constructed to find out whether the independent variables in question have an effect on the length rather than on the magnitude of the drift.

Model 2 was therefore constucted as follows:

$$L_i = \beta_0 + \beta_1 logMarketCap_i + \beta_2 IT_i + \beta_3 ConsumerDiscretionary_i + \beta_4 HealthCare_i + \beta_5 Financials_i + \beta_6 CommunicationServices_i + \beta_7 Materials_i + \beta_8 RealEstate_i + \beta_9 ConsumerStaples_i + \beta_{10} Utilities_i + \beta_{11} Energy_i + \varepsilon_i \quad (19)$$

where

L_i = Length of the drift for firm *i*, measured in days from the event date onwards so that if $AR_{i,0} \geq 0$, $AR_{i,1} < 0$ or if $AR_{i,0} < 0$, $AR_{i,1} \geq 0$, then $L_i = 0$

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, then $L_i = 1$

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, then $L_i = 2$

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$, $AR_{i,3} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, $AR_{i,3} < 0$, then $L_i = 3$

. . .

if $AR_{i,0} \geq 0$, $AR_{i,1} \geq 0$, $AR_{i,2} \geq 0$, $AR_{i,3} \geq 0$, $AR_{i,4} \geq 0$, $AR_{i,5} \geq 0$, $AR_{i,6} \geq 0$, $AR_{i,7} \geq 0$, $AR_{i,8} \geq 0$, $AR_{i,9} \geq 0$, $AR_{i,10} \geq 0$ or if $AR_{i,0} < 0$, $AR_{i,1} < 0$, $AR_{i,2} < 0$, $AR_{i,3} < 0$, $AR_{i,4} < 0$, $AR_{i,5} < 0$, $AR_{i,6} < 0$, $AR_{i,7} < 0$, $AR_{i,8} < 0$, $AR_{i,9} < 0$, $AR_{i,10} < 0$, then $y = 10$

, $L_i = 0, 1, 2, 3, \ldots, 10.$

The independent variables remain as described earlier in section *4.2.1.*

Table 11. Regression output – Model 2

Variable	*Coefficient*	*Std. Error*	*t-value*	*P-value*	*Sig.*
Intercept	1.3769	0.3734	3.6876	0.0002	**
logMarketCap	-0.0152	0.0179	-0.8537	0.3934	
IT	0.1050	0.1262	0.8323	0.4054	
ConsumerDiscretionary	-0.1036	0.1281	-0.8084	0.4189	
HealthCare	0.0696	0.1297	0.5368	0.5915	
Financials	-0.1090	0.1310	-0.8321	0.4054	
CommunicationServices	0.0698	0.1555	0.4493	0.6533	
Materials	-0.0782	0.1587	-0.4926	0.6224	
RealEstate	-0.1529	0.1611	-0.9487	0.3429	
ConsumerStaples	-0.0285	0.1703	-0.1674	0.8670	
Utilities	0.3573	0.2256	1.5833	0.1135	
Energy	0.0545	0.1790	0.3043	0.7610	

** = significant at 1% significance level
* = significant at 5% significance level

R^2 = 0.0053
Adjusted R^2 = -0.0007

Table 11 represents the regression output for *Model 2.* Compared to the three previous models, the R^2 statistics are much closer to zero (the definition for adjusted R^2 allows it to be negative but is interpreted hereby as zero), which suggests that the independent variables on the right-hand side of the model poorly explain the length of the drift. None of the independent variables are found to be statistically significant, so it can be stated that firm size and economic sector do not have explanatory power when it comes to explaining the length of the post-announcement drift.

6.3. Summary, discussion & limitations

Regarding the results of the event study, the reader should be first reminded that the observed statistically significant abnormal returns on the event date are completely in line with the efficient market hypothesis, as by defitition an efficient securities market (semi-strong form) is one where the prices of securities traded on that market at all times fully reflect all information that is publicly known about these securities. On the event date, new information comes public and the Market model used to calculate the normal returns is obviously unable to predict the nature of this information. It is therefore the abnormal returns during the days after the event date that one should focus on. Thus, it is the AARs and CAARs this study found to be statistically significant also after the event date that constitute evidence contradicting the efficient market hypothesis.

Maybe the most interesting finding regarding the event study analysis was that the GN and BN stocks were found to behave differently and thus, also the interpretation of the results differs between these two groups. The average market reaction regarding the GN stocks implies an initial overreaction to earnings information, after which the stock prices are downward-corrected. On the contrary, the average market reaction regarding the BN stocks suggests an underreaction to earnings information, as the post-announcement abnormal returns continued to be negative until the end of the event window.

Richardson et al. (2010) as well as Livnat and Mendenhall (2006) have stated that the main feature of PEAD is that investors appear to underreact to earnings announcements and consequently, a company's stock price and the cumulative abnormal returns for that stock tend to drift in the direction of the earnings news several days or even weeks after an earnings announcement. Leaning on this definition emphasizing the role of market underreaction as the determinant of PEAD, it can be stated that the anomaly was hereby found to be present only among the BN stocks. The message of this argument is to illustrate that the timeframe is of major importance as it is concluded whether PEAD is present in the markets or not. Had this study determined the event window to end on Day 2, the conclusion would have been that both of the groups experience an initial underreaction to earnings information.

Although the post-announcement behaviour of the GN and BN stocks was found to be distinct from each others, it can be jointly stated that neither of the groups behave as the efficient market hypothesis would suggest. From the theorethical perspective, it can be asked if the European stock markets in 2018 are efficient in the sense that the market participants correctly react to the earnings information so that an immidiate and a justified price correction takes place. The answer provided with this study is an unambiguous no. From the practical point of view, it can be further wondered whether the European stock markets in 2018 are efficient in the sense that arbitrage profits cannot be made. The answer is maybe not, but the final affirmation would require further examination and determination of the applicable transaction costs. This is because rational investors are willing to arbitrage the anomaly away only to the extent where the marginal costs equal the marginal benefits (Fama 1991; Jensen 1978).

To further discuss about market efficiency, it is hereby reminded that the definition of the efficient securities markets (semi-strong form) implies that publicly known information is at all times incorporated into stock prices. This implies immidiate stock price reaction to new information. This obviously is the theorethical model, and it does not take into account the fact that it surely takes at least a little time for the market parcitipants to analyze the newly announced information. Thus, it is not possible that the market at *all times* reflects all public knowledge because there occurs an inevitable delay in processing information due to human (and/or machine) qualities.

Therefore, a question rises that if the immidiate reaction *per se* is impossible, what is the acceptable time frame in which the price adjustment should be complete so that the markets can be viewed as efficient? Is it 1 minute, 6 hours, 24 hours or longer? The writer's opinion is that the definition of the market efficiency should adjust relative to the market parcitipants abilities to process information, which has undisputably increased during recent decades. If the definition of market efficiency remains unadjusted while the abilities of the market parcitipants evolve, it can lead to over-maintaining the null of market efficiency. Apparently, this problem is still to be faced as the null of market efficiency on a daily level remains at least strongly questioned if not fully rejected based on the results of this study.

The event study analysis conducted has also some limitations to it. First, the earnings surprises for the sample companies obtained from Datastream were calculated based on the average of analyst forecasts rather than historical stock prices. Thus, the observed drift classifies as AF drift and the subsequent results cannot at face value be extrapolated to be consistent with the situation where the seasonal random-walk based (RW) earnings surprise is the underlying assumption. This is also because the two distinct drifts are found to be qualitatively quite different from each others (Ayers et al. 2011). Further, when estimating the abnormal returns for the sample stocks in the event window, the betas in the deployed Market model were assumed to be stationary. As Ball, Kothari and Watts (1993) noted, this may cause a slight bias in estimated abnormal returns as betas are actually shifting upward (downward) for firms with high (low) unexpected earnings.

Table 12. Summary of the regression outputs

	Model 1a		Model 1b		Model 1c		Model 2	
Dependent var.	CAR(1;2)		CAR(1;5)		CAR(1;10)		Lenght of the drift	
R^2	0.0339		0.0499		0.0574		0.0053	
Adjusted R^2	0.0281		0.0442		0.0518		-0.0007	
Variable	*Coefficient*	*Sig.*	*Coefficient*	*Sig.*	*Coefficient*	*Sig.*	*Coefficient*	*Sig.*
logMarketCap	-0.0019	**	-0.0029	**	-0.0035	**	-0.0152	
(logRevenue)	-0.0012	**	-0.0020	**	-0.0026	**	-0.0236	
(logTotalAssets)	-0.0013	**	-0.0020	**	-0.0026	**	-0.0179	
IT								
Cons.Discretionary								
Health Care	0.0057		0.0110	**	0.0213	**	0.0696	
Financials	-0.0071	*	-0.0086	*	-0.0044		-0.1090	
Comm.Services								
Materials								
RealEstate	-0.0101	**	-0.0165	**	-0.0179	**	-0.1529	
ConsumerStaples								
Utilities								
Energy	0.0074		0.0135	**	0.0198	**	0.0545	

** = significant at 1% significance level
* = significant at 5% significance level

Table 12 further summarizes the results obtained with the OLS regression analyses. The first message of the upper part of the table is that the R^2 and Adjusted R^2 statistics mildly but gradually increased as the time period for observing the cumulative abnormal returns was prolonged (*Models 1a-1c*). This implies that firm size and economic sector explain the longer post-announcement drift slightly better than the shorter drift. Still, it has to be concluded that overall the models did not very well fit to the data and generally, the cumulative abnormal returns cannot be reliably estimated with just firm size and economic sector. The second message of the upper part of the table is that seemingly, the length of the drift (measured as days from the event date onwards) cannot be reliably estimated based on firm size and economic sector either (*Model 2*), as the R^2 and Adjusted R^2 statistics for this particular model were essentially zero.

Moving to the lower part of the *Table 12*, further conclusions can be drawn. First, *H2a* suggesting that firm size is inversely related to the magnitude of the drift was proven to be accurate with the models *1a-1c*. Hereby, it can be stated that the null H_0: $\beta_1 = 0$ is in the models *1a-1c* rejected with 99% confidence level. To further prove the point, a sensitivity analysis for the size variable $logMarketCap_i$ was conducted so that all of the regression models were re-estimated by replacing $logMarketCap_i$ with variables $logRevenue_i$ and $logTotalAssets_i$ (both in different stages to avoid multicollinearity issues). The coefficient estimates for the additional size variables were also found to be negative and significant in each of the models *1a-1c*, which is intuitive considering that using Pearson correlation, corr(*logMarketCap, logTotalAssets*) = 0.8892, corr(*logMarketCap, logRevenue*) = 0.8209 and corr(*logTotalAssets, logRevenue*) = 0.8400.

These results regarding the sensitivity analysis imply that changing the size variable does not significantly alter the conclusions, although the coefficients for $logRevenue_i$ and $logTotalAssets_i$ were generally found to be smaller than for $logMarketCap_i$. This observed negative association between firm size and the magnitude of the cumulative abnormal returns is in line with previous studies (e.g. Barber et al. 2013; Bhushan 1994; Foster et al. 1984; Garfinkel & Sokobin 2005), where PEAD was found to be stronger among smaller firms' stocks.

Table 12 further provides contradictory evidence for *H3a* suggesting that economic sector has no effect on the magnitude of the PEAD. First of all, the coefficient estimates for $HealtCare_i$ were found to be positive and significant in *Models 1b* and *1c*, suggesting that a firm operating in Health Care sector has higher intrinsic values of cumulative abnormal returns compared to a firm operating in Industrials sector, ceteris paribus. This result can be at least partly explained with re-introducing *Table 5* (below) and noting that in this case, the size variable $logMarketCap_i$ got to work through the economic sector variables, as from all of the 11 economic sectors, the Health Care sector has the second lowest median value of market capitalization. Similar (but inverse) is the situation with the Financials sector, as the median value of market capitalization for that sector is the second highest and the estimated coefficients were found to be negative and significant.

Table 5. Sector-specific descriptive statistics for Market Cap (in millions of €)

Economic sector	Median MC	Mean MC	Largest MC	Smallest MC
Utilities	2,617.93	7,484.70	52,155.07	41.77
Financials	2,274.99	8,486.05	88,409.99	40.73
Materials	1,304.05	5,491.42	84,261.24	1.09
Consumer Staples	1,109.37	10,664.90	223,139.34	8.19
Communication Services	853.80	4,260.29	70,445.78	6.07
Real Estate	831.25	2,058.09	20,967.05	13.14
Industrials	785.17	3,456.83	64,288.15	1.74
Energy	720.01	10,033.76	233,560.89	3.06
Consumer Discretionary	561.80	5,205.98	124,416.19	8.47
Health Care	298.72	4,809.17	183,717.98	2.87
IT	240.74	1,990.45	114,803.72	2.98
Total sample	666.90	5,078.79	233,560.89	1.09

However, a reasoning like this is not relevant with the Real Estate and Energy sectors, as the median values of market capitalization for these sectors do not differ much from the median value of market capitalization for the Industrials sector. Considering the Energy sector, at least a partial explanation can be offered with the fact that it is the most unrepresentative sector in the sample with n = 84. This may have distorted the power of the regression analysis and the robustness of the results.

Finally, the coefficient estimates for the Real Estate sector were found to be negative and significant in each of the models *1a-1c*. This result cannot be explained with the above arguments, so it seems that the magnitude of PEAD indeed differs between Real Estate and Industrials sectors so that the magnitude of PEAD for firms operating in the Real Estate sector is, on average, lower (ceteris paribus). This result provides mild contradictory evidence compared to previous studies, as for example Doyle et al. (2006) found that there is no significant variation in the magnitude of PEAD between different industries.

In addition, the limitations of using dummy variables have to be kept in mind when interpreting these regression results. The coefficient estimates for the sector dummies inherently tell the difference relative to the Industrials sector, but no arguments can be made e.g. on how the abnormal returns in the Financials sector differ from those of the

Utilities sector. This kind of analysis would require changing the reference category and the variables in the regression models.

For hypothesis *H2b,* suggesting that firm size is inversely related to the length of PEAD, no supporting evidence was found with *Model 2.* As stated, the R^2 and Adjusted R^2 statistics for this particular model were essentially zero and none of the coefficient estimates for the size variables used was found to be significant. Thus, with *Model 2,* H_0: $\beta_1 = 0$ is maintained with the respective significance levels. Regarding *H3b,* neither the economic sector was found to have an effect on the length of PEAD, which means that also the null H_0: $\beta_2 - \beta_{11} = 0$ is maintained with the respective significance levels. The following chart provides at least a partial explanation for this result and illustrates the limitations of *Model 2*.

Chart 3. Sample divided based on the length of PEAD

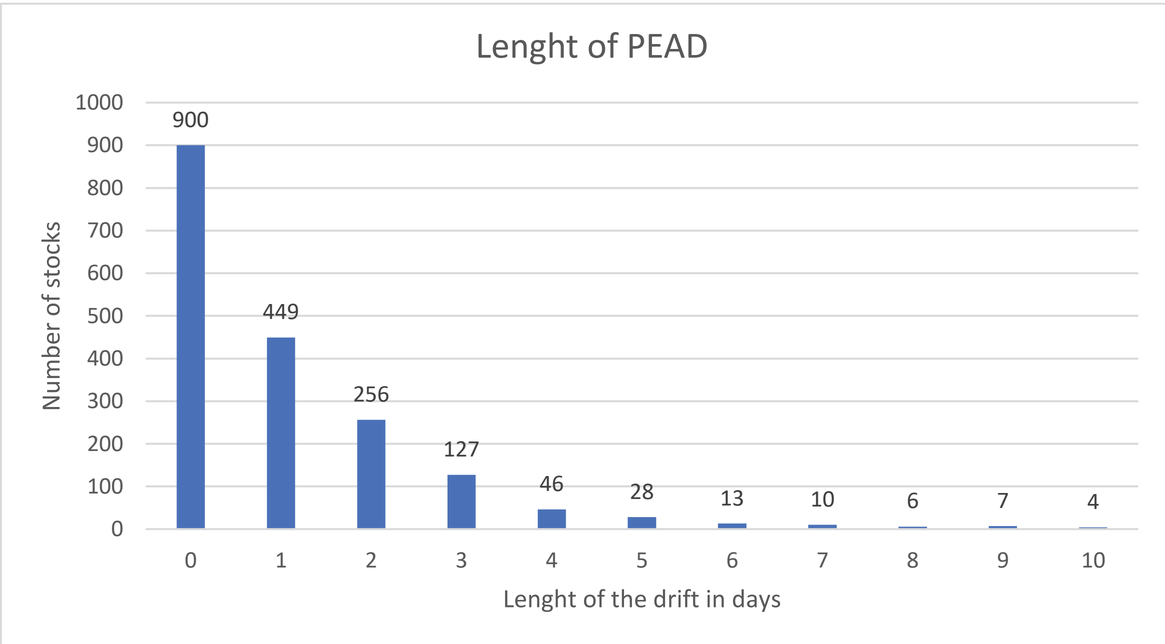


Chart 3 divides the sample based on the length of PEAD. It is observable from the above figure that almost half of the stocks in the total sample did not experience a drift at all, when the drift was measured strictly from the event date onwards. In other words, half of the sample stocks had negative (positive) abnormal returns on the event date and consecutive positive (negative) abnormal returns on Day 1. Moreover, it seems that a great majority (around 94%) of the sample stocks experienced a three-day or shorter drift.

To explain this distribution, it should be emphasized that the defitition of L_i in *Model 2* did not take the possible drift in the middle of the (0;10) window into account. This means that a particular stock may have experienced for example positive abnormal returns on all days from Day 1 to Day 10, but if that stock had negative abnormal returns on the event date (Day 0), the drift was classified to be non-existent ($L_i = 0$). Neither did the definition of L_i in *Model 2* allow the sign of the abnormal returns to change even once. This means that if a stock experienced for example negative abnormal returns on days 0-2 and further on days 4-10, but positive abnormal returns on Day 3, the length of the drift was defined to be only two days. This strict definition for the variable L_i measuring the length of PEAD may be one of the reasons why no significance was found to be present among the results of *Model 2*.

7. Conclusions

The post-earnings announcement drift is one of the most researched, yet one of the most controversial financial market anomalies found to date. The main feature of PEAD is that the stock prices do not immidiately react to earnings announcements as suggested by the efficient market hypothesis, but fluctuate in the direction of the earnings news for some time after the announcement. What separates PEAD from other market anomalies is its major persistency despite the amount of research and the attention it has gained during the past 50 years.

Originally, researches have argued whether the PEAD anomaly reflects poor risk adjustment in the underlying asset pricing models or pure market inefficiencies. Recent evidence seems to be however more consistent with the market inefficiency explanation. Thereby, the existence of the anomaly has been attributed e.g. to the level of investor sophistication as well as to the constraints set by limited attention and other psychological biases, preventing the public information to be immidiately absorbed into stock prices as the efficient market hypothesis would suggest. In addition, the existence of transaction costs seems to prevent rational investors from fully arbitraging the anomaly away. The evidence on whether investors in practice can exploit PEAD to gain net of cost arbitrage returns remains, however, ambiguous.

This study investigated the extent to which the post-earnings announcement drift anomaly is present in European stock markets in 2018, as well as how firm size and economic sector affect the magnitude and length of the drift. The results provide evidence that the anomaly is still present in the markets and is flourishing especially among the companies reporting negative news relative to what was expected by the analysts. The drift for these stocks implies an underreaction to earnings releases, whereas for the companies reporting positive news compared to what the analysts had expected, the results suggest an overreaction to earnings news. The fact that there is obvious serial correlation present especially among the abnormal returns for the bad news stocks, along the result that the markets react differently to negative and positive earnings surprises, provides evidence contradicting the efficient market hypothesis.

Moreover, it was examined if the magnitude of the post-earnings announcement drift can be attributed to firm size and economic sector. It was found that firm size is inversely related to the magnitude of the drift, which provides supplementary evidence for previous research and verifies the relation of firm size and PEAD to be accurate also in these previously quite unexplored stock markets. These results suggest that for larger firms, there exists a more immediate price reaction after the earnings announcements. For smaller firms, in turn, the delayed price response was found to be more pronounced.

The relation between the economic sector and PEAD was, however, found to be of more controversial by nature. The magnitude of PEAD was indeed found to vary between certain economic sectors, but the fact that different economic sectors have companies of different sizes prevents the conclusion that the economic sector alone causes the variation in PEAD. The only sectors between which the variation was significant and the influence of firm size on the observed variation could be at least partially ruled out were the Industrials sector and Real Estate sector.

In addition, it was examined if the length of the post-earnings announcement drift could be attributed to firm size and economic sector. The unambiguous result was that the length of the drift is not explainable by these variables. Altogether, the deployed regression models could not explain the magnitude or the length of the post announcement drift very well, which further emphasizes the complicated nature of the anomaly.

Altogehter, the results of this study further verify the fact that despite the overwhelming attention gained, this anomaly can still be found to be present in the markets while conventional attempts to find causal relations fail in searching of the primary source of the anomaly. As Bernard and Seyhun (1997) already argued, the further attempts to explain PEAD would be most fruitfully focused on reasons why market prices do not reflect all available information. This requires also additional deployment of other than quantitative methods as well as drawing from the continuosly developing trend of behavioural finance.

In addition, as for example the flash trading by computers has dramatically increased over the last decade and the microstructure of the markets is under continuous change, it can be argued that event studies using daily stock data are somewhat behind. As previous research has documented that PEAD (on daily level) is decreasing, it is recommended that further quantitative studies verged on this matter also with hourly stock data to assess the possibility of short window arbitrage profits. Nevertheless, the fundamental question of why PEAD exists is turning out to be more a matter of behavioural and social sciences than that of a quantitative economic analysis.

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